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Model Development of the Forest Quality Assessment using Second-Order Confirmatory Factor Analysis

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ABSTRACT

Forest quality plays a crucial role in sustaining the functions of forest ecosystems. This study aims to develop a valid and reliable model for assessing forest quality through six dimensions: forest productivity, forest structure, soil factors, climatic conditions, topography, and anthropogenic factors. Vegetation data were collected from 138 sample plots using a stratified purposive sampling method. Soil, topography, and climate data were obtained from the SoilGrids, DEMNAS, CHIRPS, and NASA POWER websites, respectively. Anthropogenic data were derived from Sentinel-2 imagery. The forest quality assessment model was developed using confirmatory factor analysis (CFA). Results showed that forest structure, forest productivity, soil, and anthropogenic factors are valid and reliable in assessing forest quality, with forest productivity as the primary determinant. However, topographic and climatic factors were not valid for assessing forest quality due to the low variation in topographic and climatic data within the study area. The goodness-of-fit model evaluation indicated a good fit based on criteria including the chi-square, RMSEA, GFI, SRMR, AGFI, TLI, CFI, NFI, and CMIN/DF. Based on the relative weights of each dimension and indicator and using linear additive equations, a mathematical equation for the forest quality index is derived, providing a practical framework for assessing forest quality at the landscape scale, particularly in heterogeneous tropical ecosystems.

1. Introduction

The sustainability of forest functions depends not only on the quantity of existing forests but also greatly on the quality of the forest (FAO and UNEP 2020; Kull et al. 2024). In this context, forest quality refers to the optimal value of goods and services within the ecosystem (Jiang and Yang 2023; Yan et al. 2022; Zhang et al. 2022). According to Suhendang (2020), forest quality is a sequential element in maintaining the sustainability of forests' ecological, economic, and social functions. Accurate information about forest quality is a crucial foundation for making informed decisions in forest management.

Forest quality is defined as the condition of the forest and all its attributes that can provide optimal and sustainable ecological, economic, and social benefits (Dudley et al. 2012; FAO 2024). This definition demonstrates that forest quality is an abstract and multidimensional concept, encompassing structural, functional, and socio-ecological aspects; therefore, assessment cannot be carried out directly but requires a measurable and integrated indicator approach (Han and Wan 2021). Therefore, the assessment of forest quality must be carried out using indicators that can present the attributes of forest quality (Cao et al. 2023).

Amundson and Jenny (1997) stated that forest quality is closely related to factors of the initial state of the ecosystem (such as climate, topography, parent material, and potential biota), external factors (human activities and management actions), and ecosystem age. In its development, various approaches have been used in forest quality assessment, such as Analytical Hierarchy Process (AHP) (Feng et al. 2016; Wang and Bao 2011), AHP in combination with cluster analysis (Wu et al. 2019), Exploratory Factor Analysis (EFA) and redundancy analysis (Li et al. 2020), as well as spatial econometric regression (Gu et al. 2021). The indicators used also varied, which included aspects of forest structure and productivity, ecosystem health, soil conditions, topography, and socio-economic factors. A recent study by Cao et al. (2023) and Tang et al. (2022) utilizes satellite imagery and machine learning algorithms, such as SVR, RF, CatBoost, and CNN, to map forest quality spatially. However, Guo et al. (2023) emphasized that there is no consensus on the indicators used to assess forest quality; the selection of indicators is generally adjusted to the research objectives, data availability, and characteristics of the ecosystem being studied.

At the global level, many integrative forest quality assessment models based on ecosystem indicators have been developed by Guo et al. (2023). While studies on forest quality are still scarce in Indonesia, most research remains focused on the quantity of forests (Saleh et al. 2019). The reported forest quality studies still focus on forest stands or forest soil quality (Aji et al. 2021; Manan et al. 2019; Rahayu et al. 2024; Safe'i et al. 2022). Nationally, the Ministry of Environment and Forestry (KLHK 2018) developed a method in the 2017 Indonesian environmental quality index document for assessing the quality of large-scale forests using the enhanced vegetation index (EVI) value from MODIS images (KLHK 2018). Although effective on a large scale, this approach tends to be less accurate because it generalizes indicators without considering the detailed aspects of complex forest ecosystems.

On the other hand, the complex and dynamic condition of Indonesia's natural forest ecosystem, with its high biodiversity, adds to the challenges in assessing forest quality (Hartoyo et al. 2021; Yasminnajla et al. 2023). Forest quality assessments become ineffective if all indicators are considered, as not all indicators have the same level of significance (Han and Wan 2021). Additionally, adopting an external forest quality assessment model without adequate localization can reduce the accuracy and uncertainty of the assessment results (Guo et al. 2023). Therefore, developing a forest quality assessment model suitable for the conditions of forest ecosystems in Indonesia is crucial. Given Indonesia's vast range of natural forests, a practical and affordable approach to assessing forest quality is needed, one that also achieves an adequate level of accuracy for application at the landscape scale (Han and Wan 2021). Prior studies quantitatively assessed data-driven decision-making to evaluate the implemented policy and site levels (Guo et al. 2023).

Furthermore, accurate forest quality assessment enables the effective reduction of deforestation and global change (Chen et al. 2019; Li et al. 2022). Following the description above, Rawa Aopa Watumohai National Park (TNRAW) in Southeast Sulawesi Province is a nature conservation area located in the Wallacea Zone. TNRAW is characterized by lowland forest, savanna, mangrove, and freshwater swamp ecosystems (Ridha et al. 2021). In addition, this area is also home to a diverse range of flora and fauna, including endemic species of Sulawesi (Purnomo et al. 2021; Ridha et al. 2021). The diversity of ecosystems in this area encourages the development of models used to effectively monitor and evaluate areas that are difficult to access due to strict policies.

Based on the description above, confirmatory factor analysis (CFA) is a statistical approach used to validate and assess the developed models (Hair et al. 2019; Jöreskog et al. 2016). Furthermore, CFA was used to test the relationship between latent constructs, including the accuracy of the variables (Cid et al. 2022; Hickerson and Lee 2022). It also enabled the simplification of complex models, as well as enhanced measurement instruments, to remove irrelevant items. The process focused on using the goodness-of-fit model to assess the overall model fit (Dani et al. 2022; Gómez-García et al. 2020; Ismael et al. 2021; Schweizer et al. 2020).

This research aims to develop a model of the natural forests quality using reliable and valid indicators. The proposed model efficiently and accurately assessed forest quality in several ecosystems. The results provided an effective approach capable of evaluating the natural forest qualities. Additionally, it supported sustainable forest management policies, providing a solid basis for decision-making in terms of conserving and using forest resources.

2. Materials and Methods

2.1. Study Area

This research was conducted in the Rawa Aopa Watumohai National Park (TNRAW) area located in Southeast Sulawesi Province, from August 2022 to June 2023. Geographically, the research area is located at 121°44'- 122°44' E and 4°22'- 4°39' S (**Fig. 1**). This area encompasses various ecosystems, including lowland rainforest (approximately 64,413 ha), savanna (approximately 21,617 ha), and mangrove (approximately 6,811 ha). Based on the description above, each ecosystem is characterized by varying vegetation structure, regeneration dynamics, and topography (Ramsar 2011; Ridha et al. 2021). TNRAW also faces various land use pressures, including road access, agricultural expansion, settlements, and land clearing in the buffer zone (Indra et al. 2009; Purnomo et al. 2021). Preliminary studies reported that various ecological and anthropogenic pressures led to the selection of TNRAW as an ideal location for assessing forest quality. The data acquired were processed and analyzed in the Remote Sensing and Geographic Information Systems Laboratory, Faculty of Forestry and Environment, IPB University. The litter and undergrowth samples collected in the field were analyzed at the Laboratory of the Department of Forestry, Faculty of Forestry and Environmental Sciences, Halu Oleo University.

2.2. Materials and Tools

The materials used in this study include primary data from field measurements and secondary data obtained from various valid sources. Primary data includes latent variables of forest productivity and forest structure, while secondary data includes soil fertility, topographic conditions, climatic conditions, and community activities. The tools used in this study include field survey equipment and data analysis equipment.

Equipment for field surveys consists of a working map, GPS (global positioning system), compass, 50 m plastic rope, diameter tape (phi-band), 1.3 m wooden stick, 50 m measuring tape, haga hypsometer, Suunto clinometer, machete, pruning shears, (0.5 m × 0.5 m) frame, digital scale capacity 5–10 kg, fish eye camera, ring soil sampler, soil drill, ruler, small/medium plastic bags, large size sacks, tally-sheets and stationery, and digital cameras. The equipment used for data processing includes a set of computers supported by several data processing and analysis software, namely Microsoft Excel 365, IBM SPSS Statistic, IBM AMOS 26, ArcGis 10.8.2, SAGA GIS 8.1.1, Sentinel Application Platform (SNAP), Sen2Cor_v2.10, Google Earth Engine (GEE), Image-J and Hemispherical 2.0.

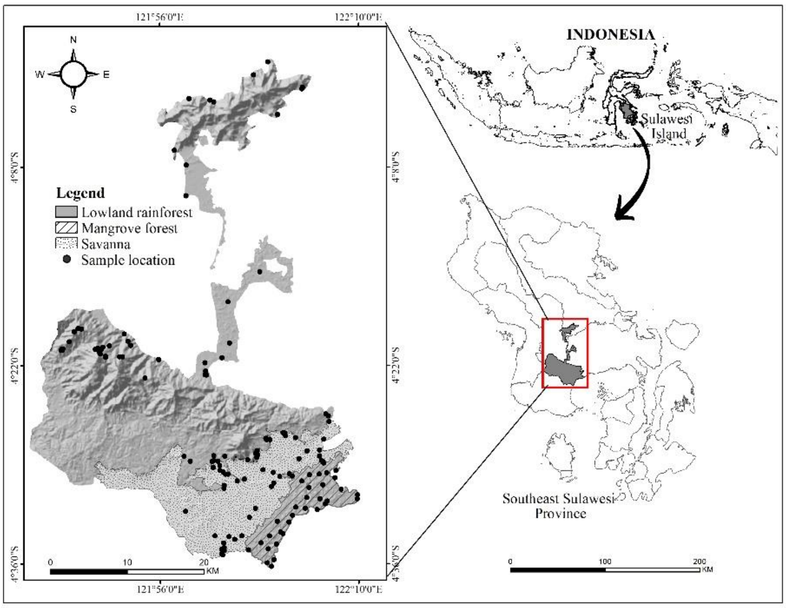
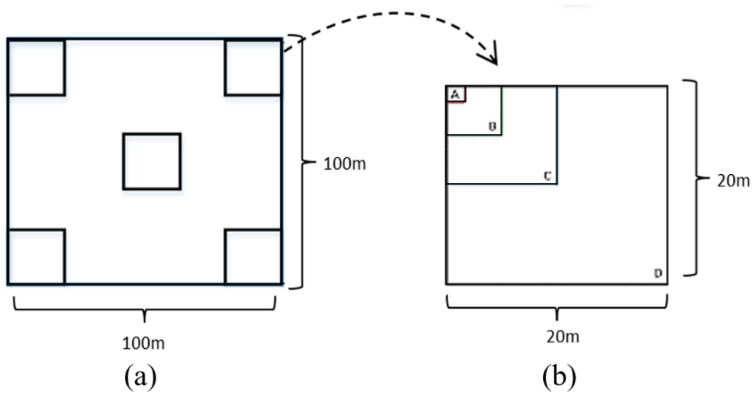


Fig. 1. Research location.

2.3. Sampling Methods

Vegetation data were collected using the stratified purposive sampling method. Stratification was carried out based on the overlay of five main spatial variables: the area management zone, the Normalized Difference Vegetation Index (NDVI) of the Sentinel imagery, site elevation, soil type, and climatic conditions, resulting in 46 unique classes of land units (strata). The combination of the five variables was chosen because of their relevance in representing ecological and biophysical variations at the landscape level. Each stratum is considered to have different ecological characteristics, but it is not assigned a special statistical weight. To ensure representativeness, three sample plots of 1 ha were purposively selected from each stratum, considering the representativeness of ecological conditions, accessibility, and ease of location accessibility. Thus, the total number of sample plots used in this study is 138.

Although the selection of sample points within each stratum is purposive, the stratification process was based on five main spatial variables, which allows a systematic and representative ecological distribution at the landscape level. This sampling design combined field ecological considerations with a spatial stratification framework designed to ensure the coverage of biophysical variation in a structured manner, even though it does not follow conventional statistical probabilities. Furthermore, in each sample plot, five observation subplots were systematically arranged (four in the corners and one in the middle), each measuring 0.04 ha, which were used to collect vegetation data based on growth phases, namely trees, poles, stakes, and seedlings. The averages of the five subplots were used to represent vegetation characteristics at each sample point. A subplot measuring 0.04 ha (20 m × 20 m) has proven to be reasonably representative in the study of vegetation structure and composition in tropical forests (Ekasari et al. 2024; Hernández-Stefanoni et al. 2018). The nested design on a 0.04 ha plot enables the cross-observation of all growth phases and a consistent spatial vegetation structure (Lin et al. 2020). In addition, the placement of 5 subplots, each 0.04 ha or 0.2 ha in size, per 1 ha plot provides a balance between the efficiency of fieldwork and the reliability of data in the context of heterogeneous landscapes (Grussu et al. 2016). The layout design of the subplots is shown in **Fig. 2**.



- Subplot A: 2x2m, for seedling, litter and understory measurements
- Subplot B: 5x5m, for sapling measurements (DBH 5 – 9 cm)
- Subplot C: 10x10m, for pole measurements (DBH 10 – 19 cm)
- Subplot D: 20x50m, for tree measurements (DBH ≥ 20 cm)

Fig. 2. Cluster (a) and observation plot (b).

Soil, topography, and climate data, respectively, were downloaded from https://soilgrids.org/, https://tanahair.indonesia.go.id, https://www.chc.ucsb.edu/data/chirps, and https://power.larc.nasa.gov/data-access-viewer/. Meanwhile, the anthropogenic data were derived from Sentinel-2 imagery. The NDVI Sentinel classification refers to the United States Geological Survey (USGS) global classification (Piragnolo et al. 2021). The data obtained was then processed using SNAP, SAGA GIS, and ArcGIS software.

2.4. Data Calculation

The results of field measurements were processed to obtain tree density data, measured as the number of individuals per unit area, and the total area of the base area (LBD), which is the total cross-sectional area of chest-high tree trunks (dbh) per plot (Li et al. 2023; Sajad et al. 2021). The height of the tree was measured with a hypsometer. According to Septiawan et al. (2017), certain criteria are used to classify the high stratification of canopy. Canopy cover percentage data were obtained by processing images produced from the fisheye camera (Bhatta et al. 2021). The volume of trees was determined as the total volume of trees in a 1 ha plot (m^3/ha). Following the description above, biomass was calculated by summing the aboveground biomass (AGB), litter, and shrub biomass (BKT), measured in tons per hectare (Kounnama and Andreou 2022). The AGB was calculated for a specific type and global model. According to Chave (2014), AGB is equivalent to 0.0673 (ρd^2H)^0.976, where D, H, and ρ describe the diameter (cm), height (m), and density (cm^{-3}) of trees, respectively (Tiryana et al. 2016). The Chave model is used for species with unverified similarities, given the heterogeneous natural forest from the study site. It also functions as a basis for the development of regional models of various tropical forests, especially in Southeast Asia (Loh et al. 2020; Yuen et al. 2016). To increase future accuracy, it is necessary to consider local calibration. The biomass calculation of litter and undergrowth biomass was performed using a general formula, which involves dividing the dry weight of the sample by its wet weight and then multiplying the result by the total wet weight (Tiryana et al. 2016). Data from various indicators used are presented in different units, so it is necessary to standardize the data using the rescaling method. For indicators without a scaling reference, data were rescaled using the rescaling score method (Kandanaarachchi et al. 2020; Shantal et al. 2023). The score scale ranges from 1 to 5, following a differential semantic scale: low (1), somewhat low (2), medium (3), suitable (4), and very good (5). The scoring process used Equation 1:

$$Score = \left[\frac{(Xi - NEmin)}{(NEmax - NEmin)} \times (NRmax\text{-}NRmin) \right] + NRmin \quad (1)$$

where *Xi* is the i variable calculation value, *NEmin* is the minimum value of the calculation of the i variable, *NEmax* is the maximum value of the calculation of the i variable, *NRmin* is the minimum value of the rescaling score, and *NRmax* is the maximum value of the rescaling score.

2.5. Data Analysis

The development of a forest quality assessment model in this study employs second-order confirmatory factor analysis (CFA), which is analyzed using AMOS 26 software. The stages of modeling and data analysis in this study are as follows:

1. Theory-based model development: Models are developed based on theoretically established causality relationships.
2. Model specification: Constructing a path diagram that includes the selection of latent variables and indicators and then defining the relationship between them.
3. Evaluation of measurement model assumptions:
   a. Sample size: The minimum sample size is 100–200 samples (Hoque et al. 2018; Kyriazos 2018)
   b. Multivariate normality: The CR value in the AMOS output is used to interpret significant deviations from the normal distribution, with significance limits of ± 2.58 for the 1% rate and ± 1.96 for the 5% rate.
   c. Outliers: Outliers are observations with extreme values that appear significantly different from other values. Multivariate normals indicate the absence of systemic extreme outliers in the combined distribution of variables, thereby minimizing interference from multivariate outliers in CFA parameter estimation (Brown 2015; Hair et al. 2019). Since the model has met the normality assumption for multivariate data, the individual variable outlier test is no longer performed separately (Ghorbani 2019).
4. Model identification: Models can be identified into three types based on degrees of freedom (df), namely unidentified (df < 0), just-identified (df = 0), and over-identified (df > 0) (Hair et al. 2019). In CFA modeling, the model is expected to be over-identified, allowing the analysis to be carried out with more data than the estimated parameters.
5. Parameter estimation:
   a. Offending estimate: Checking for the presence or absence of offending estimate, such as deficient loading factor, loading factor more than one or negative (Heywood cases), and negative or non-significant error (Hair et al. 2019; Ozkok et al. 2019).
   b. Validity and reliability test: the validity test is carried out through several steps: (1) Loading factor ≥ 0.5 (Hair et al. 2019) or loading factor ≥ 0.4 in the context of model development (Hair et al. 2022; Prudon 2015); (2) Z test or CR ≥ 1.96 at a significance level of 5%; (3) The convergent validity test with an AVE (average variant extracted) value of ≥ 0.5 or AVE

> 0.45 is considered adequate if the CR (composite reliability) ≥ 0.70 (Fornell and Larcker 1981; Na-Nan and Saributt 2020). The reliability test was conducted with a construct reliability (CR) of ≥ 0.7, which is considered very good, and a CR between 0.6 and 0.7 is still acceptable (Baharum et al. 2023; Hair et al. 2019). The calculation of the AVE and CR values is carried out using the following Equations 2 and 3:

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \theta_i} \quad (2)$$

$$CR = \frac{\sum \lambda_i^2}{(\sum \lambda_i^2)^2 + \sum \theta_i} \quad (3)$$

6. The indicator of λi is the loading factor, and θi is the error variance. Evaluate fit models: The goodness-of-fit index (GOFI) measurement was conducted using three groups of fit indices: absolute fit index, incremental fit index, and parsimony fit index (Hair et al. 2019). According to Peugh et al. (2023), the absolute fit index included the chi-square test, goodness of fit index (GFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Meanwhile, other fit index used an adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), Tucker-Lewis index (TLI), and normed fit index (NFI) (Alizadeh-Siuki et al. 2020; Lim et al. 2023). The parsimony fit index was commonly adopted as CMIN/DF, or chi-square per degree of freedom (Hair et al. 2019).
7. Improved model: When the tested CFA model does not match the data, the modification process involves removing items with low loading factors or high residual correlations (Hagum and Shalfawi 2020) and modifying the index to differentiate the inherent error indicators' correlation (Jeon et al. 2019). The modification process relied on solid theoretical justification (Fung et al. 2020; Milot-Lapointe et al. 2020)
8. Development of mathematical equations: Forest quality index measurements were conducted by adopting linear additive combination equations. This approach provided a better solution, resulting in the avoidance of complex calculations (Shyaman et al. 2024). Additionally, the forest quality index equation was formulated through the summation of each dimension responsible for assessing forest quality after it had been weighed (Brown 2015) (Equation 4):

$$FQI = \sum Wi.Xi \quad (4)$$

where *FQI*, *Wi* and *Xi* denote the forest quality index, weight, and standardized value, respectively.

The weight of each factor or dimension is the proportion of the ith factor loading percentage to the total factor loading percentage (λ) of all factors, calculated using Equation 5:

$$Wi = \frac{bi}{\sum_{i=1}^{n} bi} \quad (5)$$

where *Wi* is the weight of the i-factor, and *bi* is the percent loading of the i-factor.

3. Results and Discussion

3.1. Theoretical Model Development

The forest quality measurement model developed in this research has been analyzed using second-order confirmatory factor analysis (CFA) with the AMOS 26 software. Second-order CFA is a part of CFA analysis for the validity test of constructs involving hierarchical relationships of two-level factors: first-order factors and second-order factors (Hair et al. 2019). The exploratory factor analysis (EFA) research was not conducted, as the construct structure and indicators in the model were determined deductively based on the existing conceptual framework. The model, referred to as the state ecological factor model (Amundson and Jenny 1997), was supported by other empirical literature that explains the indicators relevant to each factor. Therefore, the use of CFA in this study can be directly employed to test the conceptual relationships that have been previously formulated, following the confirmatory approach that underlies the CFA method.

The second factor in this study was evaluated by six dimensions of the first factor, which are forest productivity, forest structure, soil fertility, climatic conditions, topographic conditions, and anthropogenic activity (Amundson and Jenny 1997). Each factor is measured by several indicators, making the forest quality construct multidimensional. The indicators used to calculate the factors in the first order are described as follows: (1) Forest productivity (PH) is measured by the above ground biomass (AGB) (PH1), tree volume (PH2), and tree base area (PH3) (Kalwar et al. 2021; Tiryana 2016); (2) Forest structure (SH) includes indicators of stand density (SH1), average tree height (SH2), canopy stratification (SH3) and, canopy cover percentage (SH4) (Felipe-Lucia et al. 2018; Gough et al. 2019); (3) Soil factor (TH) was measured through organic C (TH1), KTK (TH2), bulk density (TH3), soil texture (TH4), and soil pH (TH5) (Weil and Brady 2016); (4) Topography (TO) involves elevation (TO1), slope (TO2), slope position (TO3), and topographic wetness index (TWI) (TO4) (Jucker et al. 2018); (5) Climatic conditions denoted by IK were determined by rainfall (IK1), humidity (IK2), and wind speed (IK3) (Ferrara et al. 2017); (6) Furthermore, the anthropogenic aspect (AN) was evaluated through road accessibility (AN1), settlement (AN2), and forest area utilization (AN3) (Kumar et al. 2014; Suni et al. 2023).

The six dimensions were selected based on strong ecological relevance to the quality of forests and ecosystem services. In this context, the influence of soil on vegetation growth is a result of both nutrient availability and physical properties (Weil and Brady 2016), with moisture distribution and water flow patterns influenced by topography (Jucker et al. 2018). Preliminary studies have reported that cycles and natural disturbances, such as strong winds and droughts, are influenced by climate change (Ferrara et al. 2017). Forest structure reflects the vertical diversity and density of vegetation, which is crucial for biodiversity (Feng et al. 2020). However, forest productivity is closely linked to carbon storage capacity and related products (Chave et al. 2014; Zhu et al. 2023). Anthropogenic pressures, such as road access and land use, are primary indicators of disturbances to ecosystem stability (Kumar et al. 2014; Suni et al. 2023). These dimensions represent biotic, abiotic, and social aspects that are interrelated in influencing the sustainability of forest function and quality.

3.2. Model Specifications

The forest quality measurement model used in this study accurately reflects the actual forest conditions. A reflective model is a measurement model in which indicators manifest or reflect latent variables (Rogers and Barboza 2024). In this model, changes in latent variables result in changes in related indicators (Henseler et al. 2024). A visualization of the model's specifications, developed to measure forest quality, is shown in **Fig. 3**.

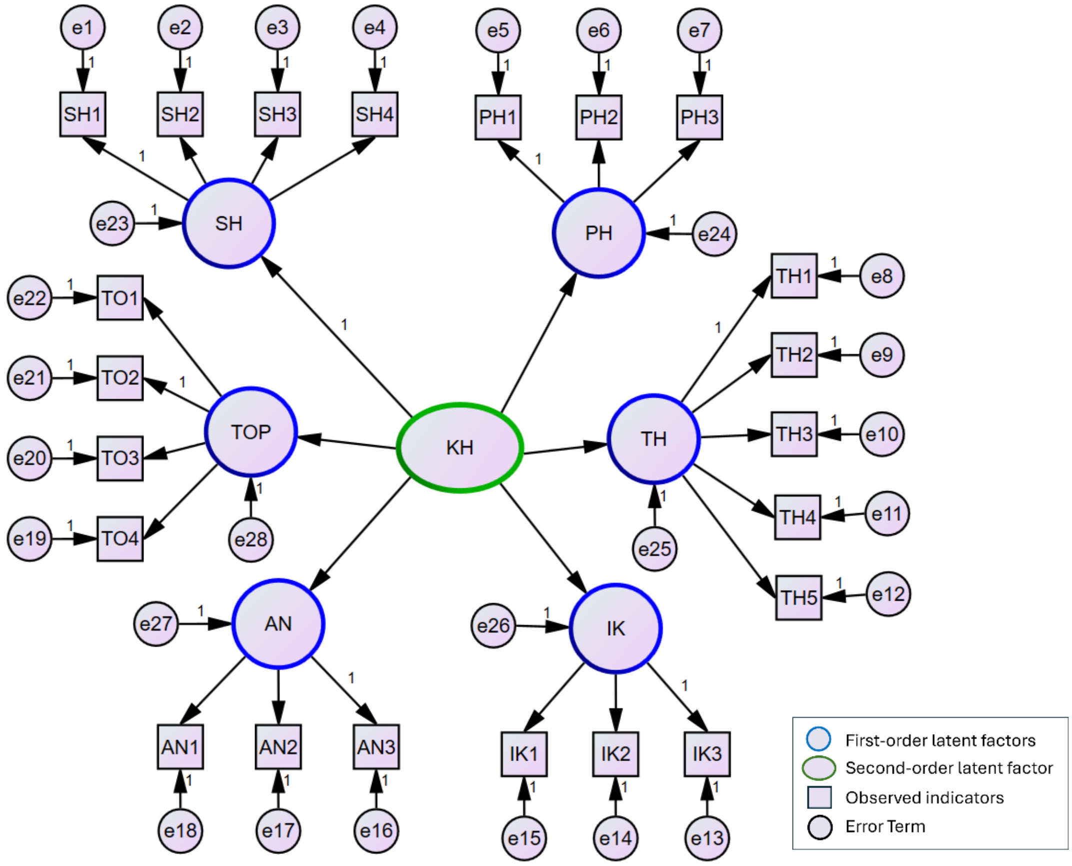


Fig. 3. Specification of forest quality measurement model.

3.3. Assumption Evaluation

The results of the evaluation of the assumptions used in the CFA are presented in **Table 1**. The table shows that the data used in this study met the requirements for sample size assumptions, was normally distributed multivariate, and was free of outliers. Thus, the analysis can be continued.

Table 1. Summary of the evaluation of assumptions used in CFA

Assumption	Result	Information
Sample size	125 samples (13 of the 138 initial data were dropped gradually to achieve normal multivariate) (Hoque et al. 2018; Kyriazos 2018)	Fulfilled
Multivariate normality	cr = -0.0.31 < -1.96; cr.kuortosis = -0.181 < -1.96 (Akram et al. 2019; Byrne 2011)	Fulfilled
Isolated	There are data with a Mahalanobis distance of 36.057, but this distance is still tolerable because the assumption of multivariate normality is fulfilled (Khan et al. 2021)	Fulfilled

3.4. Model Identification

The model identification results, performed using AMOS software, demonstrate that the aggregate number of distinct sample moments, encompassing both variances and covariances among the observed variables, totals 253. In contrast, the model requires the estimation of 50 distinct parameters, including factor loadings, variances, covariances, and potential error terms associated with the variables in the model. Consequently, this model's degree of freedom (df) is computed by deducting the number of parameters required for estimation from the total number of distinct sample (Hoque et al. 2018) moments, resulting in a degree of freedom of 203 (253–50). In this instance, a positive degree of freedom indicates that the model is over-identified. Such over-identification is pivotal, as it suggests that there is ample data to provide unique solutions for the model's parameters and to further test the model's fit. Thus, this outcome corroborates the suitability of continuing with additional analyses to refine the model and evaluate its predictive accuracy and theoretical congruence.

3.5. Parameter Estimation

Parameter estimation of the model was carried out through several respecifications to overcome inappropriate estimates and ensure the model's validity. The parameter estimation results are then visualized as a path diagram shown in **Fig. 4-6**.

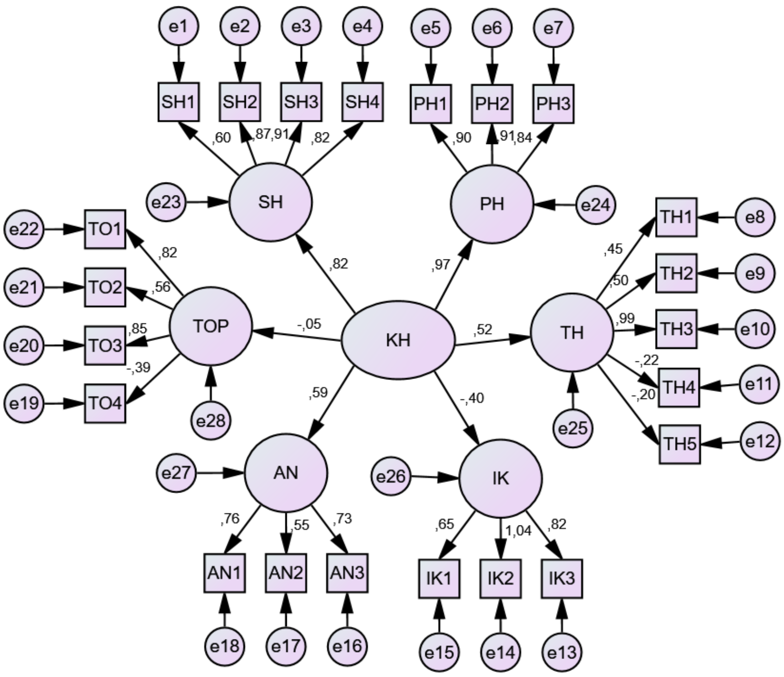


Fig. 4. The first CFA model.

The result of the parameter estimation shown in the model in **Fig. 4** indicates that the model has offending estimates, where IK2 exhibits a Heywood case (λ > 1), and the indicators TH4 (-0.22) and TH5 (-0.20) have a low loading factor. According to Hair et al. (2019), removing indicators with low loading factors or Heywood cases is recommended if they cause model instability. **Fig. 5** shows the better model after the indicator is removed. However, at the dimension level, topography (TOP) and climate (IK) cannot correctly measure the quality of forests. The topographic dimension has a deficient loading factor (0.004), and the Climate dimension shows a negative loading factor. The low loading factor in the topographic dimension is likely due to the homogeneity of the topographic conditions of mangrove and savanna ecosystems (Habibullah et al. 2023). Meanwhile, the climate factors are suspected to be caused by climate variations that are not visible due to the relatively narrow research location (Hu and Han 2022; Vandemeulebroucke et al. 2023). Low-scale data sources also contribute to the homogeneity of climate and topographic data in the study location (Pogson and Smith 2015). Linhartová et al. (2021) stated that factors with low variation can reduce the significance of their contribution to the overall model. **Fig. 6** illustrates the removal of these two dimensions from the model to improve its fit (Chew et al. 2019). Furthermore, the validity and reliability testing of the model are presented in **Table 2**.

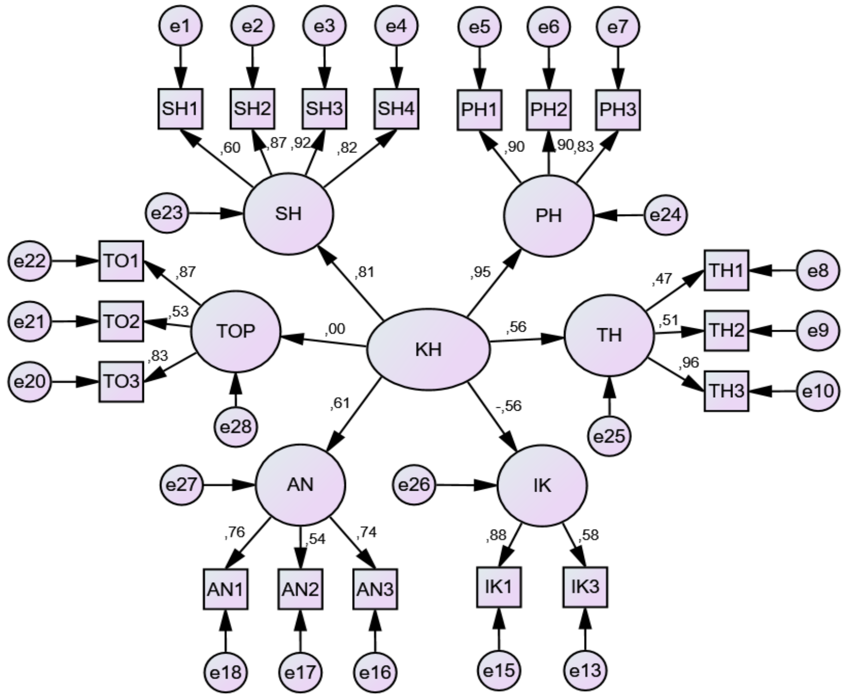


Fig. 5. The second CFA model.

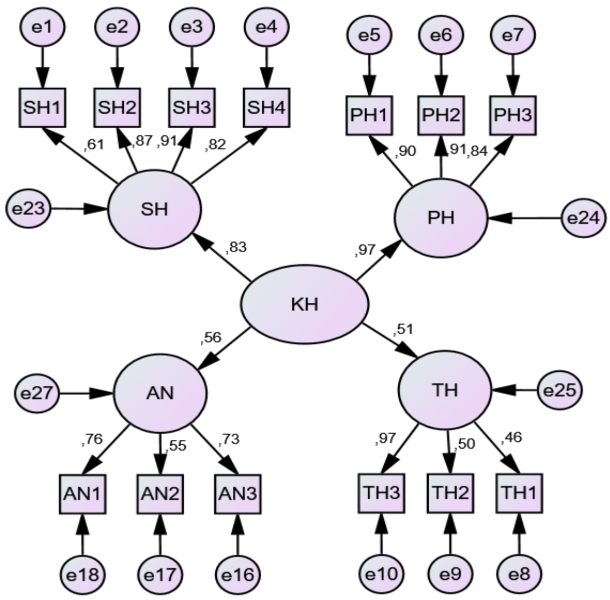


Fig. 6. The third CFA model.

Table 2 shows that all indicators are significant and valid. The loading factor significance level proved this, and Average Variance Extracted (AVE) values were greater than 5.0. However, some were slightly lower than 0.5, such as the TH and AN dimensions, requiring improvement. The Composite Reliability (CR) analysis results indicate that the reliability or internal consistency of the measurement model meets the good criteria, with a CR value of ≥ 0.70.

Table 2. Summary of parameter estimation results and calculation of CR and AVE

			Estimate	λ_i	S.E.	C.R.	P	Sig	λ_i^2	$1 - \lambda_i^2$	CR	AVE
SH	<--	KH	1	0.829				sig	0.687	0.313	0.82	0.55
PH	<--	KH	2.141	0.974	0.377	5.674	***	sig	0.949	0.051		
TH	<--	KH	0.252	0,505	0.082	3.063	0.002	sig	0.255	0.745		
AN	<--	KH	1.23	0.559	0.292	4.212	***	sig	0.312	0.688		
SH1	<--	SH	1	0.606				sig	0.367	0.633	0.88	0.66
SH2	<--	SH	1.235	0.868	0.167	7.412	***	sig	0.753	0.247		
SH3	<--	SH	1.617	0.911	0.212	7.61	***	sig	0.830	0.170		
SH4	<--	SH	1.574	0.825	0.219	7.178	***	sig	0.681	0.319		
PH1	<--	PH	1	0.895				sig	0.801	0.199	0.91	0.78
PH2	<--	PH	0.696	0.905	0.047	14.715	***	sig	0.819	0.181		
PH3	<--	PH	0.774	0.843	0.06	12.843	***	sig	0.711	0.289		
TH1	<--	TH	1	0.462				sig	0.213	0.787	0.70	0.47
TH2	<--	TH	1.028	0.504	0.244	4.215	***	sig	0.254	0.746		
TH3	<--	TH	4.429	0.973	1.094	4.047	***	sig	0.947	0.053		
AN1	<--	AN	1	0.763				sig	0.582	0.418	0.73	0.47
AN2	<--	AN	0.468	0.551	0.092	5.077	***	sig	0.304	0.696		
AN3	<--	AN	1.095	0.729	0.185	5.928	***	sig	0.531	0.469		

3.6. Model Fit Evaluation

A summary of the model fit test in **Table 3** shows that the model does not fit the data. Some major indices, such as the RMSEA of 0.138 and the SRMR of 0.848, were above the recommended tolerance limits, indicating model inconsistency with the empirical data structure. In addition, some incremental indices, such as CFI (0.805) and TLI (0.811), show only a marginal match, and the χ^2/df value of 3.346 also indicates room for improvement. This implies that, although the model is constructed based on a strong theoretical framework, in practice, it does not yet fully capture the complexity of the data. Therefore, improvement steps are necessary to enhance model compatibility. Some potential causes for low model fit include: (1) A complex and hierarchical model structure consisting of a latent second-level construct and four first-level constructs, as well as 13 observational indicators, which increases the likelihood of the emergence of unaccommodated residual correlations (Lewis 2017; Ondé and Alvarado 2018); (2) A high level of ecological heterogeneity in the study area, with 46 unique land units based on a combination of biogeophysical and socio-ecological variables. A moderate sample size has the potential to affect the stability of the estimate and lead to an increase in RMSEA (Kyriazos 2018; Lüdtke et al. 2021).

3.7. Model Improvement

The model improvement actions carried out include (1) the gradual deletion of items with high residual correlation, namely PH3(e7), SH4(e4), and SH2(e2), as well as the deletion of TH2 (e9) to avoid the Heywood case on the TH3 indicator. (2) The index modification was carried out based on the suggestion from AMOS by covariating the error of the e1 (density) and e5 (biomass) indicators. Improving the model by removing indicators is recognized as having the potential to cause overfitting, where the model becomes too specialized for the observed data and cannot be generalized to other datasets. To avoid this, cross-validation with external data that is not used to train the model is one approach that can be applied. However, in this study, the validation process could not be carried out due to the limitations of the data sample size (n = 138). This methodological limitation in this study is recommended for further testing in follow-up research.

Table 3. Model fit test results

Goodness of Fit Index	Cut-off Value	Model Results	Information
χ^2 (*Chi-square*)	90.53	204	Not fit
Probability	≥ 0.05	0.000	Not fit
RMSEA	≥ 0.08	0.138	Not fit
GFI	≤ 0.90	0.807	Marginal fit
SRMR	≤ 0.80	0.848	Not fit
AGFI	≥ 0.90	0.711	Not fit
TLI	≥ 0.90	0.811	Marginal fit
CFI	≥ 0.90	0.805	Marginal fit
NFI	≥ 0.90	0.852	Marginal fit
CMIN/DF	< 2	3.346	Not fit

However, to reduce the risk of overfitting, the elimination of indicators in this study was carried out gradually, not solely based on residual correlation values but also considering other aspects such as low loading factors and potential Heywood case symptoms, with the support of theoretical justification. Heywood cases occur when the estimation results yield statistically implausible values, such as an unfavorable error variance or a loading factor exceeding 1, typically due to multicollinearity, overlapping indicators, or a limited sample size.

The TH2 (KTK) indicator was removed because it exhibited symptoms similar to those of the Heywood case and contained a substance that overlapped with TH3 (bulk density), which adequately represents the dimensions of soil fertility (Duan et al. 2019; Endriani and Listyarini 2023). The SH2 (average tree height), SH4 (canopy closure percentage), and PH3 (tree base area/basal area) indicators were removed because their loading factor values were low compared to those of other indicators on the same dimension. This can be due to the indicator not consistently representing the contrast or dimensions it measures, or due to high measurement errors (Hair et al. 2019). Regarding SH1 (vegetation density), although the loading factor is lower than that of SH2 and SH4, it significantly improves the fit index when the index is modified by covarying the error with PH1 (Biomass). This index modification is only carried out on indicators that conceptually have a close ecological relationship. Where tree density is a direct determinant of biomass accumulation (Liu et al. 2020; Wegiel and Polowy 2020), and both were measured simultaneously in the field, so the possibility of sharing the same source of measurement error is very likely (Hair et al. 2019). **Fig. 7** presents the model visualization after improvement.

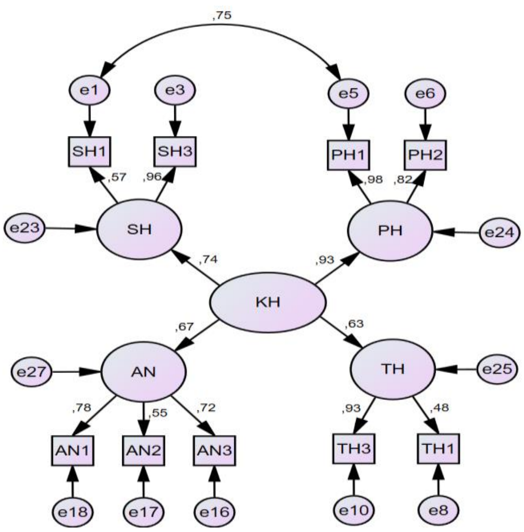


Fig. 7. The fourth CFA model.

Table 4 shows that all the indicators in the 4th model are significant and valid in explaining the construct they measure, as indicated by the loading factor and the significance level. Although TH1 has a loading factor of 0.48, this indicator is maintained in the model development context (Hair et al. 2022; Mistiani et al. 2022; Prudon 2015). The AVE value also indicates that the model has good convergent validity, with an AVE of ≥ 5.0, except for AN, which has an AVE of 0.47. In the context of exploratory research or model development, an AVE ≥ 0.45 is considered adequate if the composite reliability (CR) value is above 0.70 (Fornell and Larcker 1981; Na-Nan and Saribut 2020).

Table 4. Summary of parameter estimation results and calculation of CR and AVE

			Estimate	λ_i	S.E.	C.R.	P	Sig.	λ_i^2	$1 - \lambda_i^2$	CR	AVE
SH	<--	KH	1	0.742				sig	0.551	0.449	0.84	0.57
PH	<--	KH	2.631	0.932	0.59	4.458	***	sig	0.869	0.131		
TH	<--	KH	0.385	0.632	0.143	2.685	0.007	sig	0.399	0.601		
AN	<--	KH	1.764	0.672	0.472	3.737	***	sig	0.452	0.548		
SH1	<--	SH	1	0.574				sig	0.329	0.671	0.76	0.62
SH3	<--	SH	1.781	0.956	0.373	4.776	***	sig	0.914	0.086		
PH1	<--	PH	1	0.981				sig	0.962	0.038	0.90	0.82
PH2	<--	PH	0.577	0.822	0.049	11.804	***	sig	0.676	0.324		
TH1	<--	TH	1	0.481				sig	0.231	0.769	0.68	0.54
TH3	<--	TH	4.049	0.926	1.145	3.535	***	sig	0.857	0.143		
AN1	<--	AN	1	0.776				sig	0.299	0.701	0.72	0.47
AN2	<--	AN	0.457	0.547	0.088	5.223	***	sig	0.602	0.398		
AN3	<--	AN	1.059	0.717	0.167	6.351	***	sig	0.514	0.486		

The internal consistency of all indicators measuring construction has achieved good composite reliability, with KH having a CR of 0.84, a PH of 0.90, a SH of 0.76, a of 0.72, and a TH with a CR of 0.68. A CR of ≥ 0.70 is the best value, while values within 0.6 and 0.7 were accepted (Baharum et al. 2023; Hair et al. 2019). These results demonstrate that the dimensions of forest structure, productivity, soil, and anthropogenic factors are reliable for determining the quality of a valid forest. Additionally, the high loading factor of 0.93 suggests that productivity is the primary determinant of forest quality. Based on the analyzed perspectives, **Table 5** presents the model fit test results for the 4th CFA model.

Table 5. The results of the model fit test after the improved model

Goodness of Fit Index	Cut-off Value	Model Results	Information
χ^2 (*Chi-square*)	38.93	37.508	Fit (sig.1%)
Probability	≥ 0.05	0.021	No fit
RMSEA	≤ 0.08	0.075	fit
GFI	≥ 0.90	0.942	fit
SRMR	≤ 0.08	0.055	fit
AGFI	≥ 0.90	0.881	Marginal fit
TLI	≥ 0.90	0.943	fit
CFI	≥ 0.90	0.922	fit
NFI	≥ 0.90	0.966	fit
CMIN/DF	< 2	1.705	fit

The selection of the fit index is based on the model's ability to assess the data fit, thereby ensuring the validity of the results obtained from CFA (Knekta et al. 2019). Hair et al. (2019)

stated that at least an index from the absolute and incremental fit categories should be used to obtain a good model fit. Furthermore, Jöreskog et al (2016) reported that the evaluation results should be considered during the model development phase. Regarding the results obtained, the 4th model supports the validity and reliability of forest quality.

3.8. Development of Mathematical Equations

The coefficient values used in the mathematical equation are obtained from the CFA model and loading factors (λi). These values describe the linear relationship between the latent construct and the observed indicators. However, in the CFA framework, each indicator was the result of measurements from a latent construct and an error component. The observed variable is a linear combination of the basic latent construct and measurement error. In this category, the loading factor refers to the extent to which a latent construct can be explained by an indicator (Hair et al. 2019). The loading factor showed the proportional contribution of the forming indicator construct. The results showed that the higher the loading value, the more significant the indicator's role in representing the construct in question. This played a crucial role in developing mathematical models, as the loading coefficient served as a linear weighting factor in the formation of a composite index. For instance, in developing the Forest Quality Index (FQI), loading factors were used as weights to prepare aggregate models that were considered both mathematically accurate and ecologically relevant (Brown 2015). The research on mathematical equations measuring forest quality was developed using linear additive equations by summing the contributions of each component. The weight of its dimension was determined to normalize the loading factor value, which produces the proportion of loading dimension i and the proportion of loading indicator i, as shown in **Table 6**. This table shows the weight of each factor and indicator used in measuring the quality of the forest. Forest productivity is the most influential factor in determining the quality of global forests, accounting for about 0.31, especially through aboveground biomass (AGB), which accounts for 0.544. The forest structure is also significant, with a global weight of 0.25, dominated by canopy stratification, which weighs 0.625. The soil factor, with a global weight of 0.21, is dominated by bulk density, which accounts for 0.658 of the total weight. The anthropogenic factor has a global weight of 0.23, with the dominant indicator being the distance from the road to forest quality, which weighs 0.38. The mathematical Equation 6 for measuring the quality of the resulting forest is as follows:

$$FQI = 0.25\,(0.375SH1 + 0.625SH3) + 0.31\,(0.544PH1 + 0.456PH2) + 0.23\,(0.380AN1 + 0.268AN2 + 0.351AN3) + 0.21(0.342TH1 + 0.658TH3) \quad (6)$$

where *FQI* is the forest quality index, *SH1* is the stand density score, *SH3* is the canopy stratification score, *PH1* is the AGB score, *PH2* is the tree volume score, *TH1* is the C organic score, *TH3* is the bulk density score, *AN1* is Score of distance from the road, *AN2* is the score of distance from the settlement, *AN3* is the score of distance from forest area utilization activities.

Although the FQI model developed has undergone a structural validation process using the CFA approach, this study has not explicitly conducted an uncertainty or sensitivity analysis on the weight of indicators or dimensions. Weight uncertainty can arise from variations in loading factors influenced by data structures, sample sizes, and different local conditions. Similarly, FQI values can be sensitive to key indicators, such as changes in biomass or stand density. Therefore, follow-up studies are strongly recommended to apply evaluations or simulations that can measure weight stability and evaluate how changes in indicator values affect the final FQI value. This step will enhance the model's reliability and strengthen its application in the context of forest management decision-making.

Table 6. Weight of factors and indicators in forest quality assessment

Objective	Factors	Relative Weight	Global Weight	Indicators	Relative Weight	Global Weight
Forest Quality	Forest structure	0.742	0.25	Stand density	0.574	0.375
				Canopy stratification	0.956	0.625
	Forest productivity	0.932	0.31	AGB	0.981	0.544
				Tree volume	0.822	0.456
	Soil factor	0.632	0.21	C organic score	0.481	0.342
				Bulk density	0.926	0.658
	Anthropogenic factor	0.672	0.23	Distance from the road	0.776	0.380
				Distance from the settlement	0.547	0.268
				Distance from forest area utilization activities	0.717	0.351

As an initial foundation, the structure of the FQI model and the methodology developed in this study have great potential to be designed and integrated into national-level forest quality monitoring systems, such as the National Forestry Monitoring System (SIMONTANA), managed by the Ministry of Forestry. FQI offers a more comprehensive quantitative approach, combining various ecological dimensions and anthropogenic pressures that affect forest conditions.

With a weighted format and measurable indicators, this index can be adapted as a composite indicator to evaluate the effectiveness of sustainable forest management in various management zones or site units. Additionally, remote sensing and open-source data (such as SoilGrids, DEMNAS, and Sentinel-2) enable FQI to be deployed on a regular and cost-efficient basis. This supports efforts to strengthen evidence-based policies in forestry planning, assess the performance of permit holders, and formulate incentives for the protection of areas of high conservation value. Thus, FQI is not only a scientific tool but can also serve as a practical tool to strengthen forest governance and forest sector performance reporting at the national and regional levels.

4. Conclusions

The present study developed a forest quality assessment model using CFA. This process consisted of six main dimensions: forest productivity, soil factors, forest structure, climatic conditions, anthropogenic and topographic activities. The analysis results revealed that forest productivity, forest structure, soil factors, and anthropogenic activities are valid for assessing forest quality. The topographic and climatic factors are invalid in the context of this research area. Forest productivity, as measured by biomass and tree volume indicators, is the most significant factor in assessing forest quality. The forest structure factor was assessed by stand density and canopy stratification. The anthropogenic factors were represented by proximity to roads, settlements, and land use intensity. The soil variables consisted of organic carbon content and bulk density. The integrative approach in this study, which combines multiple dimensions, allows for a holistic evaluation of forest quality assessment. In addition, by utilizing data from various sources, including terrestrial data, SoilGrids, DEMNAS, CHIRPS, NASA POWER, and Sentinel, a comprehensive dataset will be built, enabling more accurate and real-time modeling. The use of various goodness-of-fit evaluations provides robust model validation, increasing confidence in the research. Although the developed model meets the criteria for statistical suitability, further research is needed to validate its application to different forest ecosystems. The absence of cross-validation in this study is a methodological limitation that may lead to overfitting and reduce the model's generalizability. Therefore, methodological improvements for further research are highly recommended. Given the limitations identified in the topographic and climatic dimensions, future model improvements should consider incorporating other environmental factors that may have greater significance in accurately assessing forest quality across diverse ecosystems. Integrating this model with remote sensing and machine learning technologies is highly recommended to improve the efficiency and accuracy of forest quality assessments on a larger scale.

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Z: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing – Original Draft Preparation, Writing – Review and Editing; M.B.C.: Conceptualization, Methodology, Writing – Review and Editing; B.K.: Conceptualization, Methodology, Writing – Review and Editing; T.T.: Supervision, Formal Analysis, Writing – Original Draft Preparation, Writing – Review and Editing; N.P.: Writing – Original Draft Preparation, Writing – Review and Editing.

Conflict of Interest

The authors declare no conflict of interest.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation

While preparing this manuscript, the authors used Grammarly to improve the grammar, making it easier for readers to understand. After using the tool, the authors reviewed and edited the content as necessary and take full responsibility for the integrity and originality of this publication.

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