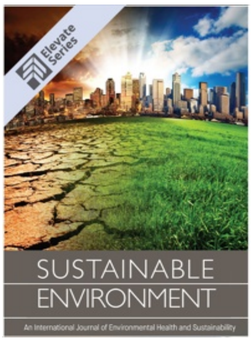

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Developing soil quality indices for predicting site classes in *Pinus patula* stands of Sao Hill and Shume Forest Plantations, Tanzania

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ABSTRACT

Soil quality indices (SQIs) are comprehensive measures of soil function, integrating physical, chemical, and biological properties, which are used globally to predict suitable sites for agricultural and forest productivity. However, a lack of information on the SQIs in East Africa, particularly in Tanzania, impacts its implementation in the forest sector. Therefore, this study analyzed soil properties and developed SQIs for predicting site productivity of *Pinus patula* stands in Tanzania. Specifically, we aimed to (i) develop SQIs under different site classes across two forest plantations and (ii) test if SQIs can predict site classes across two forest plantations and which soil physio-chemical variables inherent in the SQI contributed most to the prediction. Principal component analysis with varimax rotation was used to develop SQIs. Orthogonal partial least squares were used to test whether SQIs and soil variables can predict the site classes. Our findings show that SQIs were SCII (0.68) > SC III (0.57) > SC IV (0.56) at SHFP. Similarly, for the SFP, the values were SC I (0.67) > SC III (0.59) > SC II (0.57). The highest SQI values indicate better quality of the site class. We found that the SQIs of studied plantations fall under the intermediate soil quality (0.55 < SQI < 0.70) class. Furthermore, SQIs and some soil variables, including available phosphorus and magnesium, were identified to be the most influential variables for predicting site productivity.

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KEYWORDS
Soil quality indices; site productivity; site classes; soil properties; principal component analysis

1. Introduction

Understanding soil quality is crucial for managing soil and determining its production capacity (Andrews et al., 2002; Tian et al., 2023). It is a prerequisite for effective land resource planning and utilization (Amalu & Isong, 2017; Kalambukattu et al., 2018; Okon et al., 2019). Precision in forest and agriculture production is based on assessing soil quality to facilitate and optimize soil management and often require several soil variables to support decision-making (Mohamed et al., 2020; Roy & George, 2020). However, since some variables can also be redundant, the ability to identify critical variables can reduce both the time and costs of in situ and optimize procedures for soil assessment (Said et al., 2020). One of the most common quantitative approaches for assessing soil quality has been using the soil quality index (SQI) (Askari & Holden, 2024).

The soil quality index is commonly utilized for assessing the effects of soil management systems, cover crops, and land uses (Chaves et al., 2017; Gura & Mnkeni, 2019; Raiesi & Kabiri, 2016; Sofi et al., 2016; Yu et al., 2018). It integrates physical, chemical, and biological properties that represent the ability of soil to perform its functions such as sustaining plant and animal productivity while maintaining and/or improving air and water quality in a given ecosystem (Chaudhry et al., 2024; Elbasiouny et al., 2017; Karlen et al., 1997; Paz-Kagan, Martinez-Garza, et al., 2014). In addition, Bastida et al. (2008) highlighted the importance of incorporating physical, chemical, and biological properties in SQI assessments to effectively evaluate soil quality and improve overall site productivity.

Studies have shown that soil nutrient levels, such as organic matter content, total nitrogen, available phosphorus, and exchangeable potassium, are often used as variables in SQI and can significantly impact site productivity (Doe et al., 2010). Although there is no universally recognised approach for calculating SQI exists (Cherubin et al., 2016; Rinot et al., 2019), multiplelinear regression (Biswas et al., 2017), pedotransfer functions (Xu et al., 2017), experts' opinion, farmers' experience (Andrews et al., 2002, 2004; Lima et al., 2011; Tesfahunegn et al., 2011), and principal component analysis (PCA) (Armenise et al., 2013; Cherubin et al., 2016; Sánchez-Navarro et al., 2015) are especially useful for this purpose. PCA, for example, enables the

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reduction of dimensional complexity in large datasets, making it easier to select specific indicators by categorizing correlated soil attributes into 'principal components' (PC) groups.

The SQIs are designed to assess soil quality and predict site productivity/site classes, particularly under varying slope positions (Navas et al., 2011; Paz-Kagan, Shachak, et al., 2014). The ability of SQIs to consider spatial variability across various slope positions enhances their effectiveness in assessing soil quality. For example, SQI evaluations can capture the different moisture retention capacities and nutrient profiles of soils at varying slope position (Mulat et al., 2021). According to Meitasari et al. (2024) in Indonesia found the highest SQI in forested areas on upper slopes, while lower slopes had medium to high SQIs for grasslands and paddy fields and low to medium for dry fields and mixed gardens. Key soil properties affecting SQI include sand content, total nitrogen, pH, and aggregate stability, which are influenced by organic matter management practices tailored to specific slopes. Mesfin et al. (2022) assessed soil properties across upper, middle, and lower slope positions. Their findings revealed significant variations in soil properties such as silt content, pH, and available phosphorus, with upper slopes having the highest silt content and lower slopes showing increased organic matter and nutrient availability. The relationship between soil quality indices and slope percentage is complex, influenced by various factors including land use, vegetation type, and management practices within a given site class, highlighting the importance of site-specific management practices for improving soil quality and forest productivity (Adegbite et al., 2019; Baskan et al., 2016). Site class/site productivity in forest plantations measures the potential growth capacity of a forested area. It indicates the average height that dominant and co-dominant trees will reach a specific age in fully stocked, even-aged stands (Weiskittel et al., 2011).

Several studies have explored the relationship between SQI and site productivity (site classes) and have been widely used in crop and forest plantation studies (Fontes et al., 2003; Shen et al., 2022). Studies in China and Poland have found that SQIs can be used to predict site productivity and assess the soil fertility of forest plantations (Chodak et al., 2020; H. X. Zhang et al., 2021). Inadequate soil suitability assessment using SQIs in most developing countries has become a constraining factor in predicting sites for forest production. For example, Isong et al. (2022) in Nigeria reported that plantation lands were established primarily without resorting to adequate land use planning, causing wider differences in productivity observed across sites and hence there is a need for a collective effort to gain a better understanding of soil quality in the area, with the main goal of responsible soil management. Thus, there is a need to develop suitable soil indices to predict the quality of forest sites (Arifin et al., 2012; Sharma et al., 2005).

Despite the importance of SQIs in the forest sector, Tanzania has no comprehensive SQIs to explore its capabilities for predicting site productivity in forest plantations. Therefore, SQIs for predicting site productivity would empower forest managers to make well-informed decisions about site categorization, tree species selection, site preparation, and soil management methods. This would ultimately enhance the management and planning of forest plantations (Chen et al., 2013; Fathizad et al., 2020; Guo et al., 2017). We, therefore, hypothesize that SQI can be used to predict site productivity for forest plantations in Tanzania, and the soil physical and chemical variables inherent in the SQIs will contribute significantly to the prediction. Specifically, the objectives of the study, aimed to (i) develop soil quality indices under different site classes across two forest plantations in Tanzania and (ii) test if SQI can predict site productivity (Site class) across two forest plantations in Tanzania and which soil physical and chemical variables inherent in the SQI contributed most to the prediction.

2. Material and method

2.1. Description of the study areas

The research took place at Sao Hill Forest plantation (SHFP) in the SW highlands and Shume forest plantation (SFP) in the NE highlands of Tanzania. SHFP is located between latitude 8°18'–8° 33' S and longitude 35° 6'–35° 20' E in Iringa Region, Tanzania, and has an altitudinal range of 1400–2000 meters above sea level (m.a.s.l), averaging 1634 m.a.s.l. The area experiences an average yearly precipitation ranging from 750 to 2010 mm, falling between November and April, and mean annual temperatures ranging from 15°C to 25°C (Ngaga, 2011). Soil is underlined at depth by acidic and well-drained and of various types, mainly dystric nitrosols in association with orthic acrisols. Most of the soil originates from deeply weathered granites characterized by a sandy clay loam-rich texture graded by reddish-brown color which, contributing to its unique properties (Ngaga, 2011). The SHFP covers a total area of 135,903 ha, of which 86,003 ha are suitable for commercial tree planting and 48,200 ha is reserved for the natural forest, river valley, and future expansion (MNRT, 2018).

SFP is located in the western part of the Usambara Mountains in the Lushoto district of the Tanga region. SFP is located at 04° 40'S and 38° 15' E, an altitude range between 1650 and 2120 m.a.s.l (Lovett, 1996). The area receives two rain seasons, from September to November and from March to April, with an average annual precipitation that varies between 800 mm and 2000 mm and an average annual temperature range between 16° and 22°C (Haruyama & Toko, 2005). A minor and unreliable rain occasionally occurs in August and September. The soils are well-drained and mostly composed of clay with different levels of sand. Generally, the soil is acidic (Lundgren, 1978). The area's geology is characterized by a diverse series of ancient metamorphic rocks that belong to the Usambara system of the Precambrian. The total plantation covers about 4,863 ha.

2.2. Soil sampling

We selected the two largest administrative divisions according to production potentials in each plantation. The divisions were then divided into four compartments representing site classes (I, II, III, and IV) based on official management records and area coverage. Quadrat plots with an area of 20 m × 20 m were positioned in each site class along the soil catena based on slope position (i.e. summit, mid, and lower slopes). Soil sampling was carried out at three to four plots for each site class, resulting in 16 and 12 sampling plots (Figure 1), with 96 and 72 soil samples for SHFP and SFP, respectively. Undisturbed soil samples for determination of soil bulk density were collected using a core cylinder of known volume, while loose soil samples for determining physical and chemical properties were collected using a soil auger at depths of 0–20 cm, 20–40 cm, 40–60 cm, 60–80 cm, 80–100 cm, and 100–120 cm at five different points within each plot. The loose soil samples from each sampling depth were combined to make one composite sample. The analyzed laboratory composite samples from 0 to 40 cm topsoil layers were taken to calculate soil quality indices in the respective site classes. The topsoil, where the majority of root activity occurs, is crucial for overall plant growth. This layer typically contains the highest concentration of organic matter and nutrients that are essential to plants. Evaluating this layer is key to understanding how management practices affect soil quality and productivity (Mueller et al., 2007).

2.3. Physical and chemical properties measurement

Particle size distribution test was determined by hydrometer method as described by (Gee & Bauder, 1986), the bulk density was determined by the core method (Blake & Hartge, 1986) and the porosity was determined by assuming the soil particle density of 2.65 g/cm^3. The pH (1 M $CaCl_2$) in the soil at a solution ratio of 1:2.5 was measured by the glass electrode method following specific procedures outlined in the ASTM standards (ASTM, 1995). Soil Organic Carbon (SOC) was determined using Walkley-Black chemical oxidation procedures (Nelson & Sommers, 1996). Total nitrogen was determined by micro-Kjeldahl digestion distillation methods (Bremner & Mulvaney, 1982), while available phosphorus (P) was extracted by the Bray 1 method (Bray & Kurtz, 1945). The cation exchange capacity (CEC) was determined using the 1 mol/L NH4OAc (pH 7.0) exchange technique, followed by the leaching of ammonia (NH_3) with KCl and measured using a flame-photometer device.

The concentration of soil exchangeable bases (Ca and Mg) was determined by atomic absorption spectrophotometry (S) (Thermo Scientific, ICE Series 3500), while Potassium (K) was measured by flame emission spectrophotometer.

2.4. Estimation of site classes and soil quality assessment

The site classes for each plot were determined using the Mean Dominant Height (Hdom) of the five tallest trees of good form in each plot, as described by Vatandaşlar et al. (2023), as it changes along the soil catena within the previously assigned site classes based on slope positions (i.e. summit, mid and lower slopes). A statistics-based model was used to estimate SQIs in each plot using PCA (Mukherjee et al., 2014). The PCA model included all the original observations of soil parameters from each site class and was used as a factor extraction method in the respective site class to group the measured soil properties into principal components (PC1, PC2, and PC3) after varimax rotation (Teferi et al., 2016). Only the variables with absolute factor loadings corresponding to each of the principal components (PCs) in each site class were considered to develop a minimum data set (MDS) (Mukherjee et al., 2014). However, the PCA approach was appropriate because a multivariate correlation matrix was used to calculate the correlation coefficients between the parameters when retaining more than one variable under a specific PC.

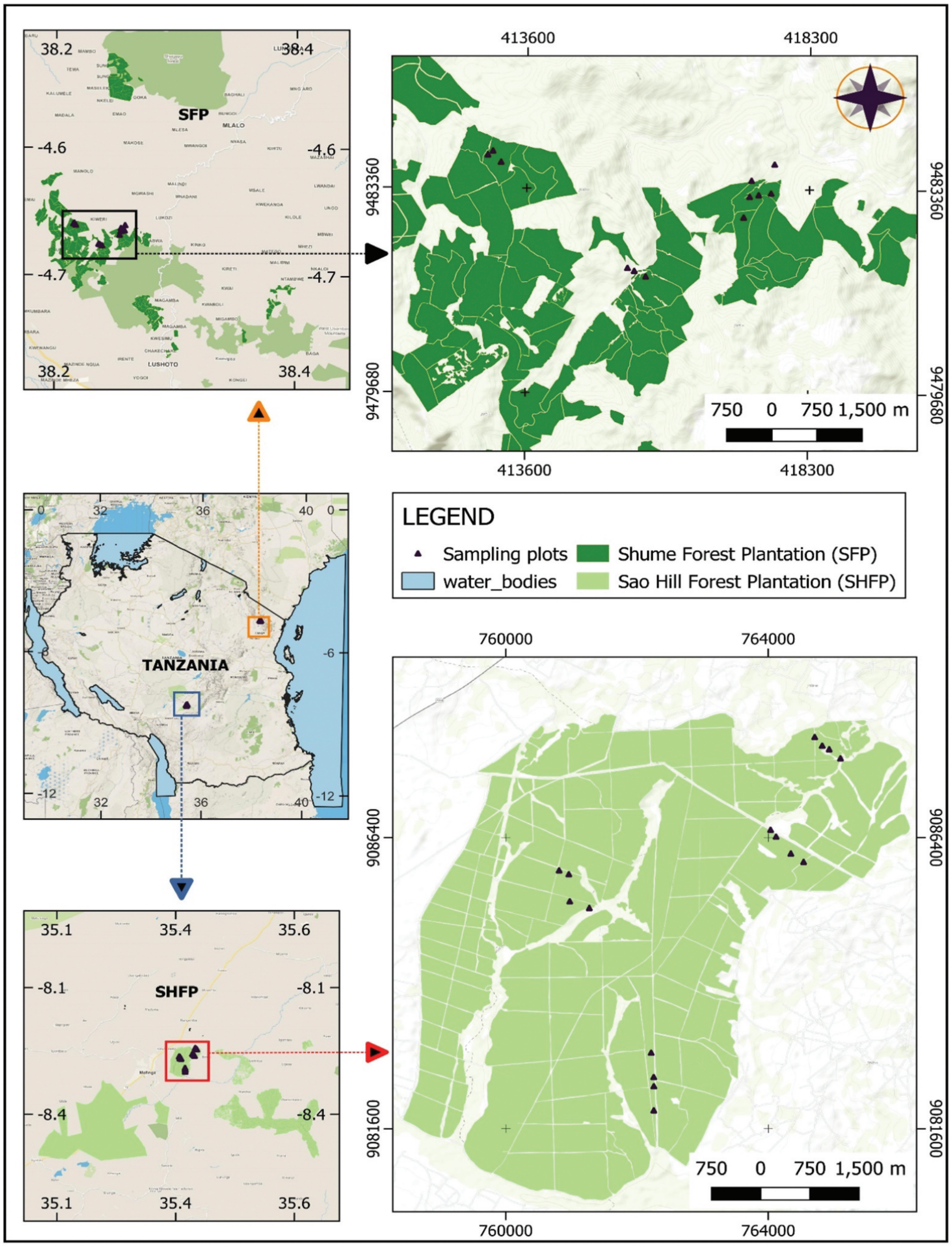

Figure 1. Locations of soil sampling plots at Sao Hill and Shume forest plantations in Tanzania.

If the parameters were significantly correlated ($r > 0.70$), then the one with the highest loading factor was retained in the MDS, and all others were eliminated from the MDS to avoid redundancy (Andrews et al., 2002; Huang et al., 2021). Each PC explained a certain amount of variation in the dataset, divided by the maximum total variation of all the PCs selected for the MDS to get a specific weightage value under a particular PC (Mukherjee et al., 2014). Next, the variables chosen in each site class were transformed into indicator score coefficients from 0 to 1. Finally, the SQI was calculated using the Cude (2001) and Masto et al. (2015) equations.

Calculation of Soil quality index for each site class

The SQI was computed using Equation (1) as outlined by Cude (2001).

$$\mathrm{SQI} = \sum_{i=1}^{N} W_i \times S_i \tag{1}$$

Wi represents the component score coefficient (CSC) derived from the PCA findings. Due to the diverse scales and units of the soil indicators, the *Si* values are normalized using a specific equation.

$$z = \frac{x - \bar{x}}{\sigma} \quad (2)$$

where z represents the standardized value, x is the value of a soil indicator, $\bar{X}$ is the average of a soil indicator, and σ is the standard deviation of a soil indicator.

Therefore, the SQI equation based on PCs can be expressed in the following equation (3):

$$\mathrm{SQI} - \mathrm{PC} = \sum_{i=1}^{N} CSC \times z \quad (3)$$

Thus, the comprehensive soil quality index (CSQI) is computed using Equation (4):

$$\mathrm{CSQI} = \sum_{i=1}^{N} VariabilityofeachPC \times \mathrm{SQI} - \mathrm{PC} \quad (4)$$

The CSQI, which is determined using z-scores, has been transformed into a standard normal distribution with a standard deviation of one and a mean of zero.

2.5. Statistical analysis

Orthogonal partial least squares (OPLS) analysis was used to test whether SQI and soil variables can predict site classes. In this analysis, site classes were assumed to be a continuous variable from 1 to 5. This is clearly not the case, but such an approximation results in better predictions than a PLS discriminant analysis of unordered classes. All statistical analyses, tables, and figures were performed using SIMCA ® software.

3. Results

3.1. Soil quality indices development for the site classes at SHFP and SFP

The PCA analysis identified three principal components for each observed site class in both plantations. These components explained (75%, 73%, 60%, 84%) and (84%, 87%, 92%, and 71%) of the variation in each PC for the total data set within the observed site classes at SHFP and SFP, respectively, this percentage provided the weight for variables chosen under a given PC (Appendix 1). Appendices 2 and 3 display the loading factors in the first three PCs in each observed site class. These loading factors summarize the initial 13 soil properties and accurately reflect the soil quality in the two plantations. The results indicated high loading values with high positive correlations for PCs in observed site class II correspond to Ca, CEC, OC, silt, BD, and TN, while PCs in observed site class III correspond to Clay and Ca, and PCs in observed site class IV correspond to AvailP, Ca, and (silt and CEC negatively correlated) at SHFP. Similarly, high loading values with high positive correlations for PCs in observed site class I correspond to pH, AvailP, silt, and K, PCs in observed site class II correspond to pH, clay, OC, and K, and PCs in observed site class III correspond to BD, K, sand, TN, and Clay at SFP. Appendices 4 and 5 show the Component Score Coefficient Matrix.

3.2. Soil quality index under different observed site classes at SHFP and SFP

We found that the SQI values for the topsoil (0–40 cm depth) were highest for SC II (0.68), followed by SC III (0.57) and SC IV (0.56) at SHFP (Figure 2). Similarly,

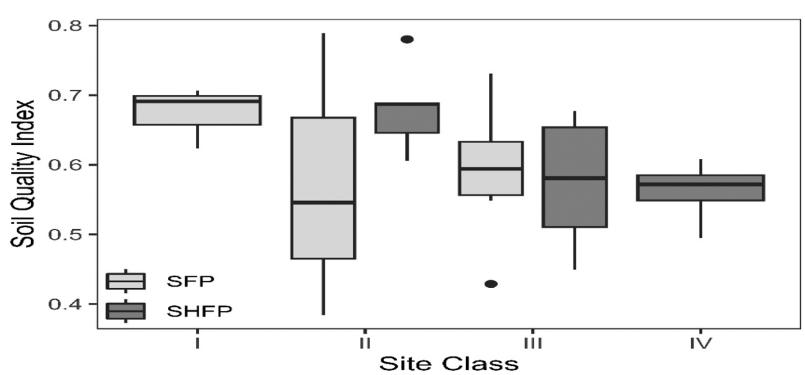

Figure 2. Soil quality index for the different observed site classes at Sao Hill Forest Plantation (SHFP) and Shume Forest Plantation (SFP) in Tanzania. The vertical line outside the box represents the minimum and maximum values. I = site class I, II = site class II, III = site class III, and IV = site class IV.

for the SFP, the SQI values were highest for SC I (0.67), followed by SC III (0.59) and SC II (0.57) (Figure 2).

3.3. Predicting site classes using SQI and soil variables at SHFP and SFP

The partial least square (PLS) resulted in the generation of one predictive component and one orthogonal component based on the cross-validation rules. The model could explain 63% (R^2Y) and predict 47% by cross-validation (Q^2Y) of variation in site class (Table 1).

The variable importance analysis (VIP) of the 18 variables used in predicting Site class revealed that magnesium (Mg), available phosphorus (AvailP), and SQI were the top three most influential variables in predicting site classes (Figure 3).

Additionally, the results of the OPLS model were significant, with confidence bars that do not overlap zero. This indicates the importance of the variables and their impact on the site class. AvailP and Mg are the most influential variables, with site and slope also affecting the site classes. Mg is negatively correlated with SQI (Figure 4)

Table 1. Cross-validation using 19 variables, 18 are X variables, and 1 is Y variable OPLS model

Components	R^2X(cum)	R^2Y(cum)	Q^2Y(cum)
Model	0.652	0.635	0.466
Predictive	0.152	0.635	0.466
Orthogonal in X (OPLS)	0.5	0	

(R^2X), the goodness of fit for the built model, (R^2Y) proportion of the response variance explained by the model and predictive performance of the model (Q^2Y).

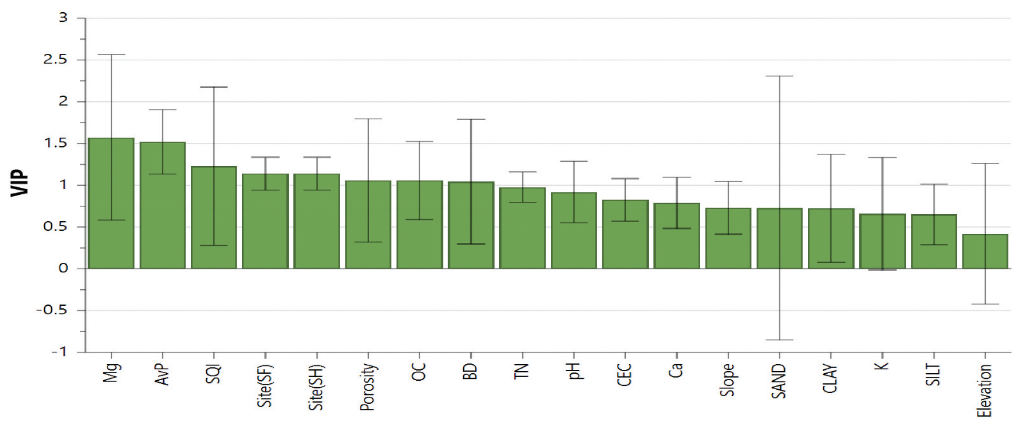

Figure 3. Variable importance projection (VIP) values for the OPLS model predicting site class from soil and site variables in P. patula stands at Sao Hill Forest Plantation (SHFP) and Shume Forest Plantation (SFP) in Tanzania. The VIP values shown are for the complete OPLS model containing both the predictive and orthogonal components and are sorted according to the predictors' importance in the model.

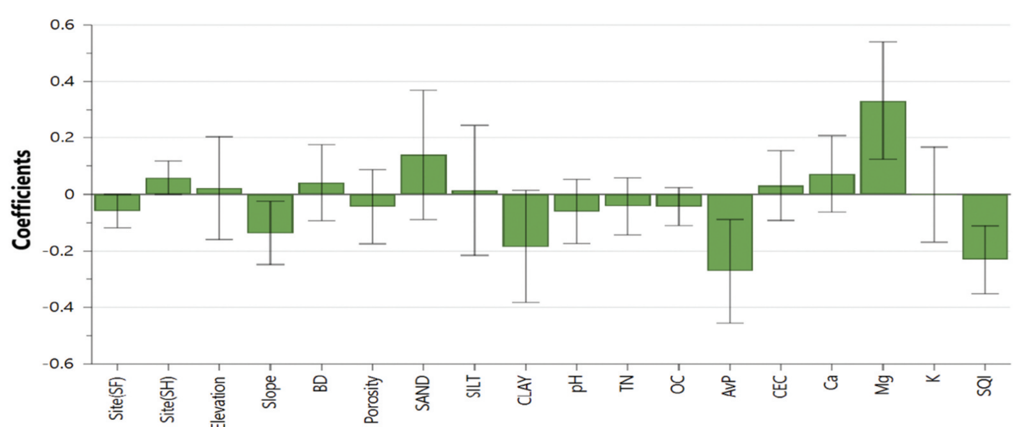

Figure 4. Correlation coefficients among the different soil indicators and SQI with site classes at Sao Hill (SHFP) and Shume Forest Plantation (SFP) in Tanzania.

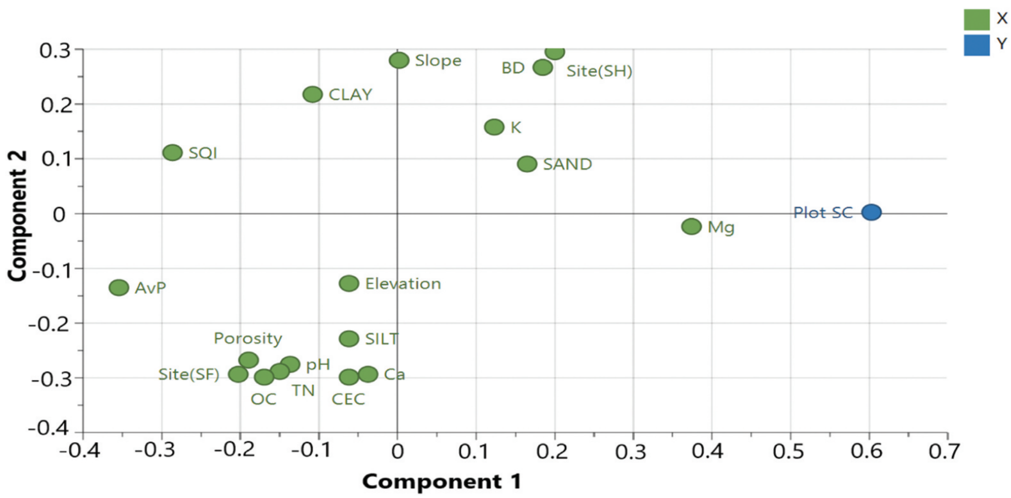

Figure 5. Loading scatter plot of the ordinary partial least squares regression (OPLS) analyses indicate a clear separation between SQI, soil variables, and topographical factors. The graphs represent the correlation between the x-variables (for SQI, soil variables, and topographical factors) and y-variables (observed site classes). The y-variable (observed site classes) is shown in blue; the explanatory variables are shown in green.

and site productivity, indicating significant implications for soil quality assessment.

Furthermore, our results clearly separated plot site classes based on SQI and soil variables in the first two components, indicating high predictability and accuracy (Figure 5).

4. Discussion

The study found that SQI was higher in site class I at SFP and II at SHFP vs. II at SFP and IV at SHFP, indicating that high SQIs contribute to better quality of the site classes. The results showed that the soils of SC II at SHFP and SC I at SFP are better off in terms of soil functioning and soil health. Better quality of the site classes improves tree growth at faster rates (Raison et al., 2001) and site classes with high SQI have the potential to produce biomass rapidly (Burger, 2004). On the other hand, the other site classes scored intermediate but with relatively lower SQI values, which indicates the need for judicious control of soil quality in the respective land use types (Nakajima et al., 2015). The SQI obtained comprises a set of indicators that reflect the balance between different physical and chemical soil properties in the site classes of the plantations (Sione et al., 2017). Thus, SQI can be used as a relative measure of site classification, ultimately enhancing forest management and planning. A high SQI value indicates fertile and healthy soil, while a low SQI value indicates less fertile soil and may require improvement (Chaudhry et al., 2024). Marzaiol et al. (2010) classified SQI into three grades: SQI < 0.55 as low soil quality, 0.55 < SQI < 0.70 as intermediate, and SQI > 0.70 as high soil quality. Supriyadi et al. (2014) proposed soil quality classes from 0.80–1 as very good, 0.60–0.79 as good, 0.35–0.59 as moderate, 0.20–0.34 as low, and 0–0.19 as very low. Comparing these grades with the soil quality classes obtained from our results, we found a good to moderate level of quality class of SQI as classified by Supriyadi et al. (2014) or intermediate soil quality as classified by Marzaiol et al. (2010). Andrews et al. (2002) and Turan et al. (2019) also observed a similar trend that a high SQI indicates better site class quality, and this is due to different soil properties that have significant effects on soil quality. A better SQI at a given site is attributed to the highly interrelated variables of high content of soil organic matter (Chandel et al., 2018), good aggregate stability, low bulk density, high cation exchange capacity, available phosphorus (Mulat et al., 2021), and associated with soil nutrient mineralization, availability, and cycling (Duval et al., 2018). The lowest SQI score was possibly due to faulty management practices, as reported by Chakraborty et al. (2019).

The SQIs have important implications in detecting the status of essential nutrients such as nitrogen and phosphorus, which are often limited in forest soils (Hatten & Liles, 2019; Obalum et al., 2017). The SQIs can help evaluate changes in the quality of forest soil and set initial levels for various soil and forest categories (Amacher et al., 2007). A study by Morugán-Coronado et al. (2013) shown that the SQI has been used in various aspects of soil quality assessment, such as the impact of land-use modification, forest management, and ecological restoration. Singh et al. (1992) found that SQIs were significantly and positively correlated with site productivity, and thus, they meet the criteria of a good indicator for enhancing forest productivity. Careful management through silvicultural site treatments that mitigate naturally compacted soils, conserving organic matter, and harvesting debris to all site classes will regulate the availability of nutrients and ensure sustainable forest productivity and health for the production of products.

On the other hand, the quality of the model was evaluated based on a goodness of fit of 65%, the proportion of the response variance explained by the model of 63%, and the model's predictive performance of 47%. These three metrics have values between 0 and 1, and the higher they are, the better the performance of the model (Dinis et al., 2022). We found that site classes differ from each other, of which SQIs and some soil variables (Mg and AvailP) contributed to site classification/prediction (Gagné, 2014). Also, with regard to VIP, Mg, and AvailP, explained variation in site classes for these two plantation sites, so these variables alone might potentially be used instead of the SQI (Recena et al., 2019). Interestingly, Mg was negatively correlated with SQI and site productivity. This finding could have significant implications for soil quality assessment in sites with highly eroded and waterlogged situations, which are probably influenced by slope positions. Using PLS Regression, Fox et al. (2007); Haywood et al. (1997); and Subedi et al. (2015) reported that Mg was a significant predictor variable for the loblolly pine (*P. taeda*) site index in the SE USA. Contrary to our study findings, Kayahara et al. (1995) explored the relationship between site and various soil nutrients and pointed out that there was no positive correlation between site productivity and soil nutrient availability, including Mg and K. Similarly to Farrelly et al. (2011a; 2011b), who developed a site index model and indicated that available K, Mg, and availP did not explain variations in the site index. Exchangeable magnesium is a vital macronutrient that can influence soil fertility and, in turn, impact forest productivity. It is a crucial element of the chlorophyll molecule, which plays a key role in photosynthesis (Bagherzadeh et al., 2018; Chaudhry et al., 2024; Rance et al., 2024).

AvailP is a very important macronutrient for plant growth (Bai et al., 2020; Zeng et al., 2019). Previously, several studies have shown that availP is the main limiting factor for tree growth in strongly acidic soils, which negatively affects root growth and soil microorganisms, thus, increasing the application of P fertilizer can effectively promote stand growth and improve soil quality in a given site class (Ma et al., 2015; Shang et al., 2020).

The model developed can essentially measure soil quality in a given site class, yet we know that soil quality will change over time as the plantation matures. Thus, the soil indices measured at stand establishment may reflect soil quality in the future. Our study successfully demonstrated that the model of SQI and soil variables can be used to predict site classes. It helps assess the overall health and productivity of forest soils. Forest managers can make informed decisions regarding land use, reforestation, and soil conservation practices by using the SQI (Díaz-Raviña & Acea, 2006). This excerpt underscores the significance of making well-informed decisions to identify the impact of management techniques on soil productivity. It also emphasizes the importance of formulating sustainable strategies for long-term forest management practices.

5. Conclusion

The present study developed soil quality indices and explored the capabilities of SQIs for predicting site classes at *P. patula* stands in SHFP and SFP, Tanzania. Our findings indicate that both the SHFP and SFP soil quality indices fall within the intermediate soil quality ($0.55 < SQI < 0.70$) class. SQIs and some soil variables, including magnesium and available phosphorus, were identified to be the most influential variables for predicting site productivity in the forest plantations. We concluded that the developed SQIs can be used to empower decision-makers to make informed choices for better forest soil management and planning to improve site productivity. Therefore, predicting site classes using SQIs are crucial due to limited resources for assessing a large set of soil properties. Making soil quality assessment requirements in policies simple and affordable are important, primarily as most developing countries aim to expand the forest sector, ultimately paving the way to sustainably meet the growing demand for wood products.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Author's contributions

Data collection, data curation, formal analysis, methodology, writing original draft and writing—review and editing JM. Conceptualization, Data curation, methodology, writing-revision and editing of the main manuscript IU, JZK, and conceptualization, data curation, methodology, writing—review and editing the manuscript, SMM.

Data availability statement

Data will be made available on request.

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