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The Classification of Land Quality Index Using Minimum Data Set – Study in a Tropical Agroecosystem of East Java

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ABSTRACT

This study aimed to identify the factors influencing land quality in a tropical agroecosystem of Jember Regency, East Java, Indonesia, using a minimum data set approach. A principal component analysis (PCA) approach was employed to derive a minimum data set from various land parameters, including soil texture, bulk density, soil depth, pH, CEC, SOC, available P, available K, drainage, slope, surface rock, irrigation infrastructure, erosion hazard, flood hazard, annual temperature, and climate type. Data from 105 sampling locations were analysed to calculate the land quality index (LQI). The study found that six parameters significantly represent land quality: SOC (30.4%), effective soil depth (19.8%), available P (17.0%), available K (13.0%), erosion hazard (10.7%), and pH (8.9%). Long-term use of organic fertiliser can enhance land quality and prevent degradation. The study was limited to the Jember Regency and may not apply directly to other regions without adaptation. The findings can guide sustainable agricultural practices and land management in tropical regions, particularly in areas facing similar climatic and soil conditions. This study provides a quantitative assessment of land quality using a minimum data set in a tropical agroecosystem, filling a gap in the literature and offering a model for other regions to adopt.

Keywords: tropical agroecosystem, land quality assessment, principal component analysis, soil health indicators, sustainable agriculture.

INTRODUCTION

Tropical agriculture is an agricultural system in tropical areas, namely areas located around the equator. Tropical ecosystems are known for their hot and humid climate throughout the year, with average temperatures that tend to remain constant. These conditions create an ideal environment for various agricultural and horticultural crops (Agegnehu et al., 2021). However, the area is subject to force by high rainfall intensity during the rainy season and less rainfall during the dry season. Moreover, the length of the seasons and rainfall intensity vary from one year to another. The El Nino and La Nina oscillations influence this condition. Therefore, sustainable agricultural practices in these tropical regions are more complex due to the effect of climate change, the decrease in soil fertility, and the value of farm products that are still not favourable finally, the social and economic background of the majority of small farmers add the complexity of this problem.

Singh et al. (2020) stated that tropical agriculture faces considerable challenges. Some are climate change, land degradation, and pest and disease problems. Changes in rainfall patterns and temperatures can affect crop yields and land productivity. Tropical agriculture has great potential to support global food security and local economies. Properly managed tropical areas can become the world's food basket while maintaining ecosystem balance and biodiversity. The land quality index (LQI) can also be viewed as one of the components of the agroecosystem sustainability hierarchy. When management objectives focus on sustainability and not on crop yields (Taghizadeh et al., 2020; Triantafyllidis et al., 2018). In addition, Mandal et al. (2021) stated that various factors, such as management practices, soil characteristics and climate, influence land quality. Several studies also state that soil quality, climate and management influence land quality (De Laurentiis et al., 2019; Lenka et al., 2022; Werner et al., 2020resulting in self-reinforcing feedback to the global climate system. We investigated additional consequences of SOM reduction for soil water holding capacity (WHC). Consequently, a holistic data set of land health indicators must include soil quality, topography, terrain conditions, and climate.

Jember Regency, located in East Java Province, Indonesia, is known as one of the regions with a very productive agricultural sector. With a supportive tropical climate, Jember has extensive and fertile farming land for crops such as rice, coffee, cocoa, tobacco, and vegetables. Agricultural management in Jember is dominated by intensive management (Alfarisy et al., 2020). Excessive use of chemical fertilisers produces residues, accumulates over decades, and causes soil acidity, reducing crop production.

This research aimed to evaluate the land quality in Jember Regency by analysing 16 different land parameters. The central hypothesis posits that assessing land quality through 105 soil samples using a specific minimal dataset will yield sensitive indicators capable of accurately describing land quality in tropical agroecosystems. This study represents the initial effort to quantify land quality using an index that integrates soil conditions, climate, topography, and land characteristics within tropical agroecosystems, with a strong focus on agro-environmental sustainability.

MATERIALS AND METHODS

Research study

The study area covers the Jember Regency (3,293.34 km²) and spans an altitude range from 0 to 3.330 masl (Fig. 1).

Geographically, it is span between 113°15’46” – 114°2’34” East Longitude and 7°58’7” – 8°33’45” South Latitude. Jember is forced by a tropical climate with distinct hot and rainy seasons, an average temperature of 28.1 °C, and an average annual precipitation of 2.766 mm.

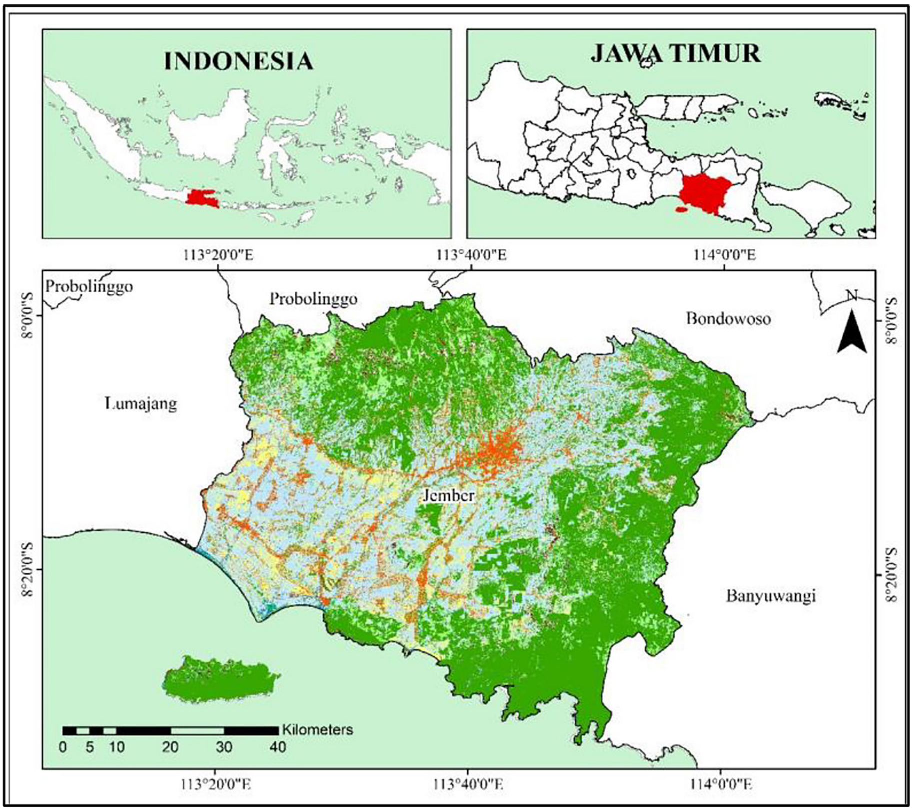

Figure 1. Land use and land cover maps of the study area

Jember significantly contributes to the national food supply, boasting Indonesia's largest harvest area, productivity, and rice production (BPS-Statistics Indonesia, 2021).

Input data

The data utilised in this study encompassed a digital map detailing the tropical agroecosystem, along with maps of soil types, slopes, flood occurrences, temperature, rainfall, surface rocks, irrigation infrastructure, erosion hazards, and soil quality. Table 1 provides details on the acquisition and sources of this data. The tools employed in the research included GIS software, Excel, SPSS, and laboratory analysis equipment.

Procedures

The processing procedure of mapping the land quality index involves the following steps: (1) creating land use and land cover maps, (2) conducting field surveys and laboratory analyses, (3) scoring land quality parameters, (4) assessing land quality using principal component analysis (PCA), and (5) mapping the land quality index.

Land use land cover maps

The land use land cover (LULC) map is interpreted from Sentinel images (Figure 1). Sentinel-2 images covering the areas of interest from 2020 to 2021 were sourced from www.usgs.gov. The data included Sentinel-2 MSI (01-01-2020) and level-2A S.R. (31-09-2021), utilising all bands. The images were processed using Google Earth Engine (GEE) (Mandala et al., 2024) and QGIS (Indarto et al., 2020).

In GEE, pre-processing tasks involved filtering for minimal cloud cover, mosaicking, compositing, image enhancement, and clipping. The image composites included bands 2, 3, 4, 5, 6, 7, 8, 8A, 11, and 12 (green, blue, red, red edge 1-4, SWIR-2, NIR). The final composite image was then downloaded and exported to QGIS. In QGIS, supervised classification was performed using the classification tools, employing a support vector machine (SVM) algorithm (Zhang et al., 2018; Mandanici and Bitelli, 2016; Huang et al., 2016)the recently launched Sentinel-2A satellite provides a new opportunity for moderate spatial resolution burned area mapping. This study examines the performance of the Sentinel-2A multi spectral instrument (MSI. Approximately 140 training areas were used to facilitate the supervised classification process. The result was a land cover map of the area of interest clipped to the administrative boundaries.

Field surveys and laboratory analysis

Land attributes include topography, terrain, climate, and soil quality. Land data was collected on 35 locations on 100×100 m plots and divided into five sections (Figure 2). One hundred five composite soil samples were taken to a 0-30 cm depth. The soil sample was air-dried, ground, and sieved through a 2.00 mm sieve and used to analyse soil properties such as soil pH, K, P, CEC, Tx, B.D., and SOC. Land attributes measured in the field include E.D., D, S.F., and I (SNI 1964:2008 2008; Eviati and Sulaeman 2009). Other land attributes such as E.H., F.H., CT, and T were analysed from secondary data. Table 2 shows the land

Table 1. Research data

No	Input data	Data source
1	Land use map	Sentinel-2A. satellite image processing and classification https://earthexplorer.usgs.gov/
2	Soil type map	Agricultural Research and Development Agency of Indonesia https://www.litbang.pertanian.go.id/produk/68/
3	Slope map	Digital elevation model (DEM) Processing and classification from the National Geospatial Agency website. https://tanahair.indonesia.go.id/demnas
4	Flood hazard from 2016–2020	Disaster Management Agency
5	Rainfall from 1999–2020	77 climate stations in Jember Regency
6	Temperature	Water resources management technical implementation unit
7	Irrigation infrastructure condition	Field survey
8	Surface rock	Field survey
9	Erosion hazard	Data processing using the USLE method
10	Soil properties	Field measurements and laboratory analysis

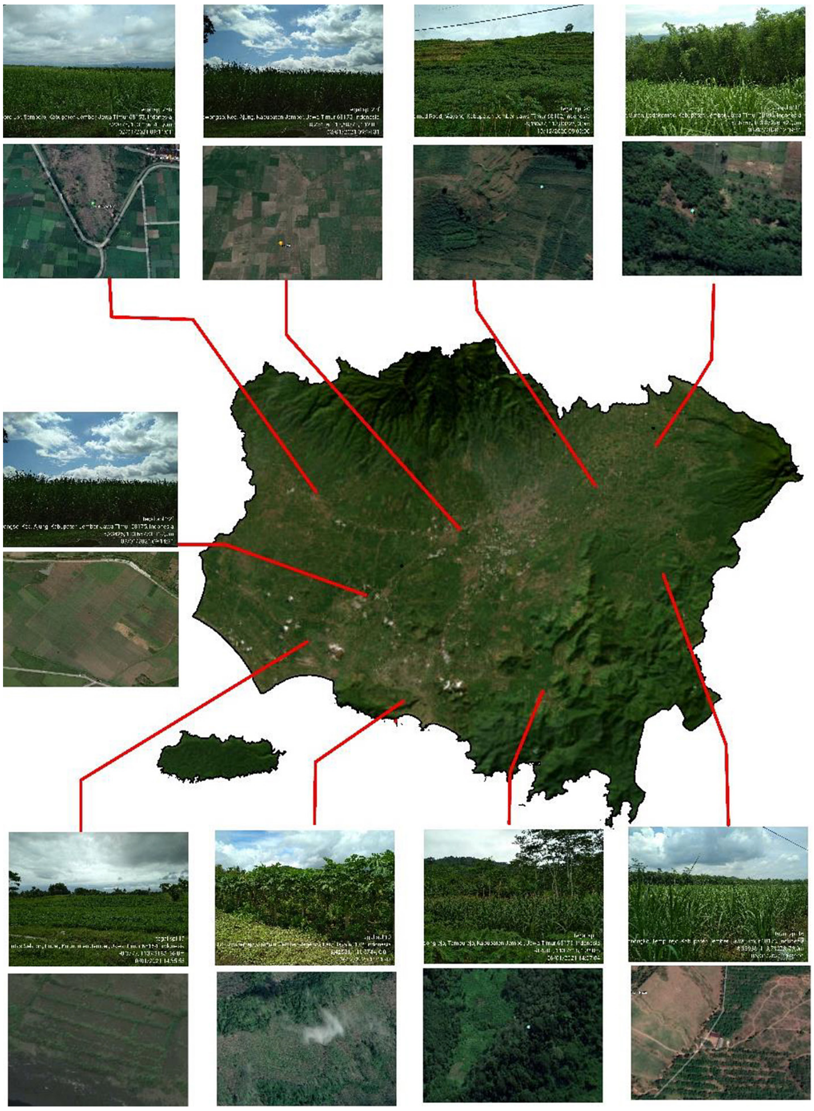

Figure 2. Sampling location

Table 2. Land and soil attribute analysis methods

Parameter	Abbreviation	Unit	Method
pH	p		The soil-water suspension (1:5)
Available of phosphorus	P	ppm	Olsen and Bray
Available of pottasium	K	cmol kg^{-1}	NH4OAc extract
Cation exchange capacity	CEC	cmol kg^{-1}	NH4OAc extract
Texture	Tx		Pippet
Bulk density	B.D.	g cm^{-3}	Gravimetry
Soil organic carbon	SOC	%	Walkey and Black
Soil depth	S.D.	cm	Field measurement
Drainage	D		Field measurement
Surface rock	S.R.	%	Field measurement
Irrigation infrastructure	I		Field measurement
Erosion hazard	E.H.	t ha^{-1} yr^{-1}	Usle
Flood hazard	F.H.	event	Modified topographic index
Climate type	CT		Inverse distance weighting (IDW)
Annual temperature	T	°C	Inverse distance weighting (IDW)

and soil and the analytical methods used (Eviati and Sulaeman, 2009; Bieganowski and Ryżak, 2011); USDA, 2011; Ritung et al., 2011; Wischmeier and Smith, 1987; BNPB, 2016there are four of science principles in Qur'an. Among of them are: istikhlaf, equilibrium, and taskhir principles. The concept of science and technology in Qur'an is also applicable and relevant to be applicated in learning process at Islamic education institution. But, there is still a problem in it, i.e. the problem of educational dichotomy. The problem can be solved by integration project in education. It can be elaborated in three issues: 1).

Scoring of land quality parameter

Land attributes that have been analysed were then scored. Scoring is a decision-making technique that involves various factors by giving a score or value to each factor. The weighting of the land quality parameter is based on the criteria of Ritung et al. (2011), which can be seen in Table 3.

Land quality assessment using principal component analysis

The PCA method has been employed for quality assessment in various regions, i.e., Erbil Province (Maulood et al., 2020), India (Vasu et al., 2016; Edrisi et al., 2019), Punjab (Chandel et al., 2018)a study was conducted to address the selection of most appropriate soil quality indicators and to know the status of soil quality in the area under different land uses. Principal component analysis (PCA, Citarum (Mulyono et al., 2019). PCA is used to identify minimum data sets (MDS) that accurately represent land quality information. The PCA analysis procedure typically involves selecting the MDS, normalising

Table 3. Scoring of land quality index parameters for tropical agroecosystem

No	Land parameters	Unit	Interpretation	Level	Score
A.	Soil quality				
1	Ph		Severely acid/alkaline-almost no plants can grow in this environment	4.0–4.5; 8.0–8.5	1
			Strongly acid/alkaline - only the most acid/alkaline tolerant plants can grow in this ph range and then only if organic matter levels are high enough to mitigate high levels of extractable possible B and other oxyanion Al and other metals toxicities	4.5–5.1; 7.5–8.0	2
			Moderately acid/alkaline – growth of acid/alkaline intolerant plants is affected depending on levels of extractable Al and other metals. Possible P and metal deficiencies	5.1–5.6; 7.0–7.6	3
			Slightly acid/alkaline – optimum for many plant species, possible deficiencies of available P and some metals (for example, Zn)	5.6–6.0; 6.5–7.0	4
			Near neutral – optimum for many plant species expect those that prefer acid soils	6.0–6.5	5
2	Available P	ppm	Very low	5–10	1
			Low	42278	2
			Moderate	15–25	3
			High	25–35	4
			Very high	> 35	5
3	Available K	cmol kg^{-1}	Very low	0.05–1	1
			Low	0.1–0.3	2
			Moderate	0.3–0.6	3
			High	0.6–1	4
			Very high	> 1	5
4	CEC	cmol kg^{-1}	Very low	2–8	1
			Low	8–16	2
			Moderate	16–25	3
			High	25–40	4
			Very high	> 40	5

Cont. Table 3.

5	SOC	%	Very low	0.5–1	1
			Low	1–2	2
			Moderate	2–4	3
			High	4–5	4
			Very high	> 5	5
6	Texture		Very rough, does not form balls and rolls, and does not attached.	Sandy soils (coarse soil)	0
			A bit rough, forms a rather strong ball but crumbles easily, too a biy sticky	Loamy soils (moderately coarse texture)SL	1
			Heavy taste, forms a perfect ball, very hard when dry, wet is very sticky.	Loamy soils (medium teture)	2
			Very rough, forms balls that are easily crushed, and somewhat attached.	Loamy soils (medium texture)	3
			The slippery feel is a bit rough, forming a ball when dry is difficult twisted, easy to roll, and sticks.	Clayey soils (fine texture) CS, Si, lsi, csi	4
			Clear slippery feel, forms a firm ball, rolls shiny, sticks	Clayey soils (fine texture) C, lcsi, sic, LCS	5
7	Soil depth	cm	Very shallow	< 30	1
			Shallow	30–40	2
			Moderately	40–80	3
			Deep	60–80	4
			Very deep	> 80	5
8	Bulk density	g cm^{-3}	Gravel	> 1.6 (gravel)	1
			Sand	1.4–1.6 (sand)	2
			Organic silt	1.2–1.4 (organic silt)	3
			Anorganic clay	1.1–1.2 (anorganic clay)	4
			Organic clay	0.8–1.1 (organic clay)	5
9	Drainage		Soil with very low hydraulic conductivity and very low water holding capacity, permanently wet soil and flooded for quite a long time up to the surface.	Very poorly drained; Excessively drained	0
			The soil has low hydraulic conductivity and low to very low water holding capacity, soil wet for a long time long enough to reach the surface.	Poorly drained	1
			The soil has conductivity rather low hydraulics and low to very low water holding capacity, soil wet to the surface.	Somewhat drained	2
			Soil has moderate to slightly low hydraulic conductivity and low water holding capacity, wet soil close to the surface. Such soil is suitable for various crops.	Moderately well drained	3
			The soil has moderate hydraulic conductivity and strength hold moderate water, moist, but not wet enough near the surface. Land Thus it is suitable for various plants	Somewhat excessively drained	4
			Soil has high hydraulic conductivity up to very high and low air holding capacity. Such land is not suitable for plants without irrigation	Well–drained	5
B.	Topography				
10	Slope	%	Very step	>40	0
			Step	25–40	1
			Hilly	15–25	2
			Rolling	8–15	3
			Undulating	2–8	4
			Flat	<2	5

Cont. Table 3.

C.	Terrain				
11	Surface rock	%	Huge	> 60	0
			Much	30–60	1
			Somewhat much	15–30	2
			Moderate	8–15	3
			A little	2–8	4
			None – a little	< 2	5
12	Irrigation infrastructure condition	Water loss (%)	There are no irrigation structures	No irrigation infrastructure	0
			There are irrigation buildings with a level of damage weight, supply water < 25%	> 75	1
			There are irrigation buildings with damage moderate-somewhat weight, supply water 25–50%	50–75	2
			There are irrigation buildings with minor damage, water supply 50–75%	25–50	3
			There are irrigation buildings with water supply interruptions of 75–95%	5–25	4
			There is, round the clock water supply	< 5	5
13	Flood hazard in 5 years	Event	Very vulnerable	5	0
			Prone	4	1
			Somewhat vulnerable	3	2
			Light	2	3
			Very light	1	4
			Without flooding	0	5
14	Erosion hazard	$t \cdot ha^{-1} \cdot yr^{-1}$	Very light	<15	1
			Light	15–60	2
			Moderate	60–180	3
			Heavy	180–300	4
			Very heavy	> 300	5
D.	Climate				
15	Annual temperature	°C	Bad for plant growth	< 19	1
			Less for plant growth	19–22	2
			Sufficient for plant growth	22–25	3
			Good for plant growth	25–28	4
			Very good for plant growth	> 28	5
16	Climate type based on oldeman		Wet months that last less than 3 months	E	1
			3 to 4 consecutive wet months	D3, D4	2
			Consecutive wet months between 5 and 6 months	C3, C4, D1, D2	3
			Consecutive wet months for more than 9 months	C1, C2, A1, A2	4
			Consecutive wet months between 7 and 9 months	B1, B2	5

the data, and integrating the indicator scores into the land quality index. PCA helps reduce data redundancy by selecting land indicators with eigenvalues greater than 1 for the MDS. Data normalisation is performed using a linear scoring function. In this study, the normalisation follows the "more is better" approach, where each observation is divided by the highest observation score, resulting in the highest value receiving a score of 1 and all others receiving scores less than 1. Each MDS is then assigned a weighting factor (Wi) by dividing the variance percentage by the total variance percentage.

Land quality index mapping

LQI mapping was conducted using GIS software through the following steps:

1. The values and weights of the land indicators from the MDS were added to the SHP file of the sampling locations.
2. The values and weights of the land indicators from the MDS were added to the SHP file of the sampling locations. Interpolation was performed on each MDS indicator using the Inverse Distance Weighted (IDW) method. This technique calculates cell values at unsampled locations through a linearly weighted combination of sample points (Hadi and Tombul, 2018; Zhang et al., 2022)
3. The interpolation results were then processed using a raster calculator, summing the scores of each indicator multiplied by their respective weights. The formula for determining the land quality index (LQI) is given by:

$$LQI = \sum_{i=1}^{n} Wi \times Si \quad (1)$$

where: Wi – weighting factor; Si – the indicator scores for variable i.

4. The raster calculator results were then classified using the reclassify tool in QGIS to determine the land quality classes (Table 4) based on Sari et al. (2022).

RESULT AND DISCUSSION

Accuracy assessment

The accuracy assessment findings (Table 5) demonstrate encouraging outcomes for the produced map. The OA achieved was 93.62%, while the K.A. accuracy was 90.70%. P.A. and U.A. values ranged between 84 to 100. The lowest accuracy assessment value is observed in S.H. In contrast, the highest is in O.W. S.H., which exhibits lower accuracy due to its real-world mixing with other classes in the field, making differentiation challenging.

Land use and land cover classification results

The land cover map (Fig. 3) generated from the classification processes illustrates eight distinct classes: built-up (B.U.), plantation (P), paddy field (P.F.), agricultural land (A.L.), forest (F), bare soil (B.S.), open water (O.P.), and wetland. Tropical agroecosystems (P.F. and A.L.) constitute over 40% of the total area in the Jember Regency, while vegetation (V.G.) covers more than 40% of the entire region. A detailed breakdown of the land cover classification results can be found in Table 6.

Results of land parameter analysis

In Figure 4 shown the result of land parameter analysis. Based on the study's results, the land quality condition in Jember Regency is known. Each land parameter has a different value at each location except for the Al parameters, which can be exchanged. Al ex is the aluminium level in the soil; Al in exchangeable form is generally found in acidic soils with a pH < 5.0. This aluminium is very active because it is in the form of Al^{3+}, which is detrimental by poisoning plants or binding phosphorus. The average pH of the study site was 7.1, which is included in the neutral category.

Principal component analysis result

Table 7 presents the PCA results for evaluating LQI. Six principal components (P.C.s) with eigenvalues greater than 1, derived from various land attributes, collectively explain 77.5% of the variance. These P.C.s represent six key land

Table 4. Land quality classes

No	Score	Class of LQI	Interpretation
1	0.86–1.00	Highly suitable (s1)	The land has no significant or fundamental limitations for ongoing use or minor limiting factors that do not substantially reduce its productivity.
2	0.76–0.85	Moderately high (s2)	The land has limiting factors that affect productivity and require additional inputs. However, these obstacles are generally manageable by farmers.
3	0.66–0.75	Marginal suitable (s3)	The land faces significant limiting factors that impact its productivity, particularly in S3. Addressing these limitations necessitates substantial capital investment, making it difficult for farmers to overcome them independently. Therefore, government or private sector intervention and assistance are necessary to mitigate these challenges.
4	0.41–0.65	Unsuitable (N)	Land classified as unsuitable (N) exhibits extremely severe limiting factors or presents challenges that are difficult to overcome.

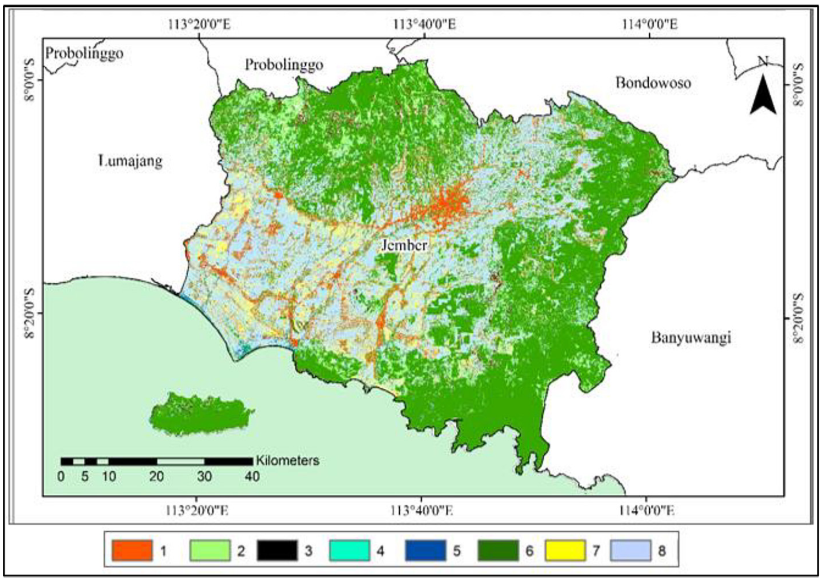

Figure 3. Land use land cover in the study area

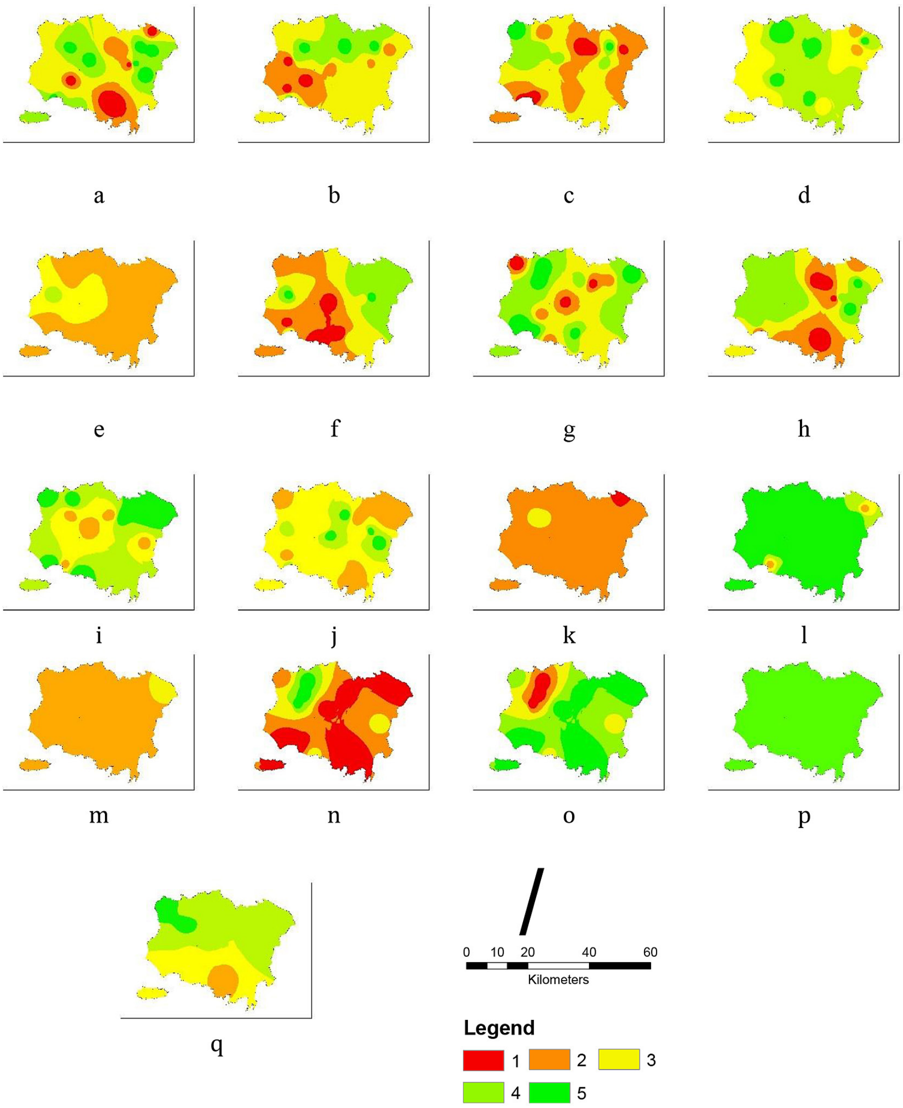

Figure 4. Distribution map of (a) S, (b) S.R., (c) TBE, (d) F.H., (e) II, (f) T, (g) C.T., (h) E.D., (i) Tx, (j) B.D., (k) D, (l) pH, (m) CEC, (n) P, (o) K, (p) Al-ex, (q) SOC.

Table 5. Land use land cover accuracy assessment

Assessment	Classes									
	BU	AL	BS	PF	OW	VG	SH	WL	OA	KA
UA (%)	96	96	97	96	90	91	86	87	92.27	90.70
PA (%)	100	99	82	91	94	93	84	82		

Note: U.A. – user's accuracy, P.A. – producer's accuracy, O.A. – overall accuracy, K.A. – kappa accuracy.

Table 6. Land use land cover class of the AOI

No	Classes	km²	%
1	Built-up	205.4	6.2
2	Plantation	231.7	7.0
3	Bare soil	37.4	1.1
4	Paddy field	1071.4	32.5
5	Open water	13.6	0.4
6	Forest	1,462.5	44.4
7	Agricultural land	257.1	7.8
8	Wet land	8.0	0.2
Total	3,293.0	100.0	

parameters: SOC, SD, P, K, E.H., and pH. The weighting factor for each P.C. is determined by dividing the percentage of variance it explains by the total variance. The trend of weighting factors for the MDS follows PC1 (0.30) > PC2 (0.20) > PC3 (0.17) > PC4 (0.13) > PC5 (0.11) > PC6 (0.09). The LQI is calculated by multiplying each P.C. score by its respective weighting factor derived from the PCA, as shown in Equation 2:

$$LQI = 0.30\ PC1 + 0.20\ PC2 + 0.17\ PC3 + 0.13\ PC4 + 0.11\ PC5 + 0.09\ PC6 \quad (2)$$

Land quality plays a pivotal role in agricultural production, as demonstrated in this study through six indicators: SO, E.D., P, K, E.H., and pH. Each of these parameters serves a vital function in supporting crop growth. SOC, in particular, exerts a significant influence on the physical, chemical, and biological properties of soil. Previous research by Trifan (2018) highlighted that potassium availability is the primary factor explaining most observed variability in soil health. Moreover, studies by Vasu et al. (2016) and Raiesi (2017) with the latter being inherently linked to pedogenic processes.

Table 7. The principal component analysis result

Land parameter	Component					
	PC1	PC2	PC3	PC4	PC5	PC6
pH	0.47	-0.29	0.23	-0.12	0.16	0.57*
SOC	0.76*	0.09	0.04	0.37	0.07	0.03
P	0.49	-0.08	0.54*	-0.01	0.34	0.19
K	0.65	-0.14	0.08	0.46*	-0.20	-0.03
CEC	0.65	0.55	-0.18	-0.07	-0.10	0.20
Tx	0.49	0.40	-0.01	-0.41	-0.44	-0.04
ED	0.09	0.80*	0.10	-0.06	-0.04	-0.05
BD	0.70	0.01	0.06	0.41	-0.02	-0.31
D	-0.28	0.41	0.45	0.41	0.21	-0.19
S	0.10	0.38	-0.74	0.13	-0.11	0.09
RS	-0.20	-0.25	-0.70	0.14	0.37	0.21
FH	-0.46	0.21	0.37	0.12	-0.41	0.57
I	0.35	-0.15	0.11	-0.82	0.01	-0.19
EH	-0.08	0.49	0.19	-0.21	0.53*	-0.07
CT	0.67	0.28	-0.27	-0.15	0.35	0.17
T	-0.67	0.59	-0.02	0.08	0.15	0.11
Eigen values	0.30	0.19	0.17	0.13	0.10	0.08
% of Variance	25.32	14.81	12.08	11.18	7.59	6.45
Cumulative %	25.32	40.13	52.22	63.41	71.00	77.46

Note: extraction method – principal component analysis.

Two different SQIs were estimated for soil surface (0–15 cm) have underscored the accurate description of soil quality through properties such as electrical conductivity (EC), pH, and SOC. SOC's role extends to facilitating water movement, enhancing water availability and retention, improving soil aggregate stability, reducing erosion, and supplying plant nutrients (Werner et al., 2020; Murphy, 2015). Carbon stored in the soil also contributes to various functions critical for biomass production, water storage, filtration, biodiversity maintenance, and other ecosystem services (Yang et al., 2015) Hebei Province, China. The dominant cropping systems are winter wheat–summer corn rotation. There were totally sixteen treatments applied to both wheat and corn seasons: inorganic fertilizers as main plots and corn stalks as subplots and the main plots and subplots all have four levels. The results revealed: after 22 years, mixed application of inorganic fertilizers and crop residuals, the SOC and crop yields substantially increased. Higher fertilizer application rates resulted in greater crop yields improvement. In 2002–2003, wheat and corn for the highest fertilizer inputs had the highest yield level, 6400 $kg \cdot ha^{-1}$ and 8600 $kg \cdot ha^{-1}$, respectively. However, the SOC decreased as the excessive inorganic fertilizer input and increased with the rising application of corn stalks. The treatment of the second-highest inorganic fertilizer and the highest corn stalks had the highest SOC concentration (8.64 $g \cdot C \cdot kg^{-1}$).

E.D. is how plant roots can still enter the soil. The more profound the adequate soil depth, the wider the root area and plant root uptake (Han et al., 2021)and determine the relationship between FRP and net primary production (NPP. Soil depth also affects root dispersion, water-holding capacity, and the ability to provide plant nutrients (Clemente et al., 2019; Sulieman et al., 2018). Palawija plants will grow well if the effective soil depth is over 50 cm (Ritung et al., 2011).

Phosphorus in the study site was in the very high category. The high available P is influenced by continuous and excessive P input, so there is still a lot of P left in the field. Nagumo et al. (2013) stated that in rice fields in Japan, there was an accumulation of available P for two decades, which could damage the environment. The accumulated P content is included in the high category. The results of the nutrient balance analysis showed that Japanese farmers only needed to add 20 kg/ha/year of phosphorus. Based on the interviews, farmers use excessive P fertiliser in the 200–250 kg/ha range.

Potassium is absorbed by plants in the form of K^+ ions. K element has a valence of one, so the K element is easily leached, which causes the availability of K nutrients in the soil to be low (Banerjee et al., 2018). In addition, the type of fertiliser used also affects the leaching of K. Using single fertilisers resulted in more nutrients being leached than using compound fertilisers (Senyigit et al., 2011). One effort that can be made to improve the efficiency of K fertilisation is the addition of organic matter. Applying organic matter increased K availability and reduced the amount of K leaching.

The E.H. level of land is also a measure of land quality. The E.H. level is influenced by plant and their management, erosion or rainfall, and soil and slope factors (Taslim et al., 2019). Erosion is one of the most significant causes of land degradation. Erosion causes a reduction in the soil layer and decreases soil fertility (Mandal et al., 2021; Zhou et al., 2018). The total loss of N, P, and K elements due to erosion on oil palm land in Sorolangun Regency was 0.04, 0.11 and 0.10 tons/ha/year (Mustikasari et al., 2018). Generally, the study site's E.H. ranges from 15–60 tons/ha/year.

pH measures the number of hydrogen ions in a solution in the soil. pH dramatically affects soil fertility and plant survival. pH will affect translocation, trace elements, mobility of organic matter, and soil biological processes (Neina, 2019). Plants generally absorb nutrients well at neutral pH. At this pH, all macronutrients are maximally available, while micronutrients are not maximised except for molybdenum (Mo), so it is necessary to add micronutrients (Karapouloutidou and Gasparatos, 2019).

Assessment of land quality index

Land quality shows the diversity of interactions between human and environmental factors. Improved land quality shows the land's ability to support agricultural production, thereby improving the economy and social status of the community. Figure 5 shows the distribution of agricultural land quality in Jember Regency. There are 14,189.6 ha belonging to the marginally suitable class (1A), 44.052 ha to the moderately suitable class (1B), and 43,310.5 ha to the highly suitable class (1C).

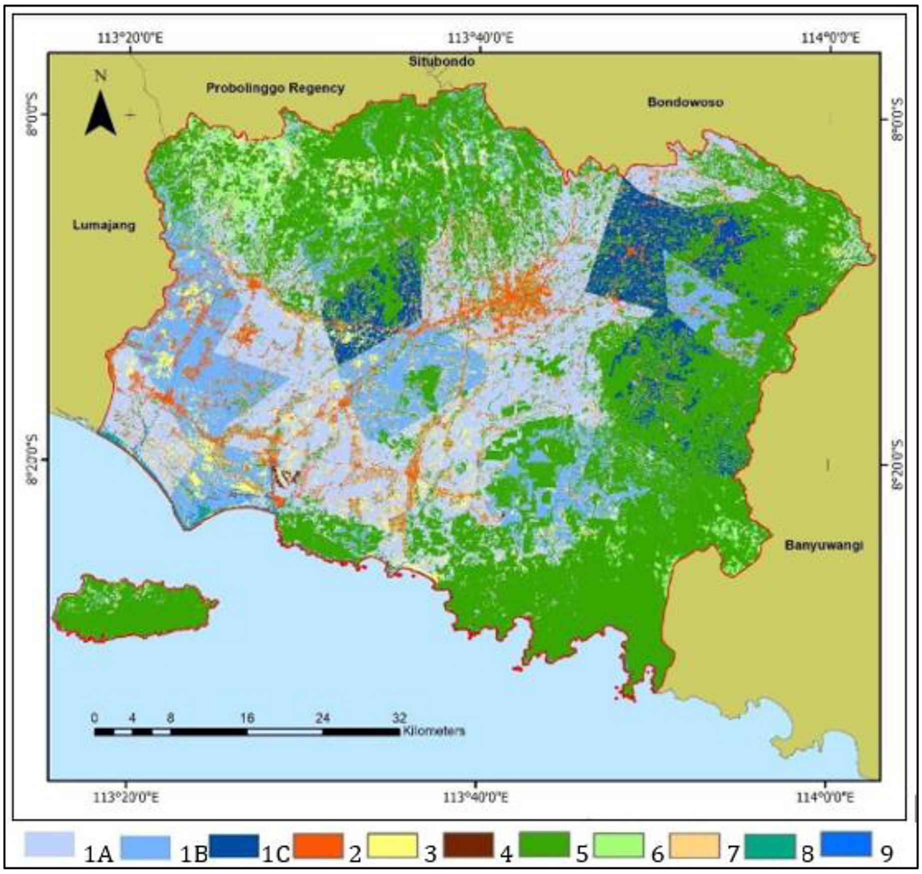

Figure 5. Distribution of land quality

The land quality index can be used as a basis for the planning process of a region (Senes et al., 2020). Characteristics of the land used include slope, S.R., TBE, F.H., I, T, CT, E.D., Tx, B.D., Drainage, pH, CEC, P, K, Al-dd, and SOC. The analysis results show that there is 14,189.69 ha (14.88%) belonging to the marginally suitable class (1A), 44,052.04 ha (44.20%) to the moderately suitable class (1B), and 43,310.58 ha (42.92%) to the highly suitable class (1C).

Marginally suitable land is distributed across the districts of Tempurejo, Ledokombo, Jelbuk, Mayang, Sumberjambe, Sukorambi, and Tempurejo. Moderately suitable land is found in Umbulsari, Ambulu, Rambipuji, Wuluhan, Bangsalsari, Jombang, and Puger districts. Highly suitable land quality is observed in the Jenggawah, Tanggul, Mumbulsari, Kencong and Semboro districts. This distribution highlights the necessity for site-specific soil management practices to enhance soil quality and support plant growth.

Areas classified as highly and moderately suitable can serve as reserves for food agricultural land, as they still possess sufficient land capability to sustain crop production (Nabiollahi et al., 2017; Sari et al., 2022; Zhang et al., 2022). Conversely, regions with marginal suitable land quality could be designated as reserves for residential development with appropriate conservation efforts. Although these areas have limited potential for plant growth, they can still accommodate human settlement. The growth of plants relies heavily on land quality, as Budiyanto et al. (2019) emphasise. Hence, there is a pressing need for targeted soil management strategies to enhance soil quality and promote plant survival.

Organic matter amendments can be employed to address these limitations. Organic fertilisers can enhance nutrient availability and improve soil texture, particularly in the future (Murphy, 2015; Yang et al., 2015; Karapouloutidou, 2019). Furthermore, organic matter additions facilitate humus formation, which acts similarly to clay and significantly contributes to the increased availability of P and K (Singh et al., 2020). The carbon stored in soil plays a crucial role in supporting various soil functions essential for biomass production, water retention, filtration, biodiversity preservation, and other ecosystem services (Murphy, 2015; Yang et al., 2015).

CONCLUSIONS

The study successfully identified key indicators of land quality in a tropical agroecosystem using a minimum data set approach. The principal component analysis revealed that the most critical factors are SOC, effective soil depth, available P, available K, erosion hazard, and pH. This research fills a quantitative land quality assessment gap and opens prospects for similar studies in other tropical regions. The long-term use of organic fertilisers is recommended to maintain and improve land quality.

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