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# Land Suitability Evaluation for Sustainable Tea Cultivation: A Machine Learning and AHP Integrated Approach

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## ABSTRACT

*Land suitability evaluation is essential for achieving efficient and sustainable use of land resources. This study applied a multi-criteria decision analysis by integrating soil spatial information generated by using Random Forest (RF) model with climate, topography, land cover, and accessibility factors in the Analytical Hierarchy Process (AHP) framework to evaluate land suitability for tea cultivation in Ganyange Ward, Tarime District, Tanzania. Key soil properties relevant to tea growth were predicted from environmental covariates using RF model and integrated with climate, topography, land cover, and accessibility data*

*in the suitability assessment process. AHP based on expert judgment was used to determine the relative priority weights of criteria in the suitability evaluation. The overall tea suitability map was generated using a weighted overlay approach within a geographic information system (GIS) framework. The AHP ranking identified climate as the most influential factor (0.37), followed by soil chemical properties (0.25), soil physical properties (0.18), topography (0.12), land cover characteristics (0.05), and accessibility (0.03). The overall suitability analysis indicated that 4.99% of the study area is highly suitable, 63.16% moderately suitable, 31.80% marginally suitable, and 0.06% not suitable for tea cultivation. To enhance suitability, integrated soil fertility management, and improvement of soil organic matter are recommended.*

**Key words:** Land Suitability Evaluation, Tea Cultivation, Digital soil mapping, Random Forest, Analytical Hierarchy Process

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## 1 Introduction

Tea (*Camellia sinensis* [L.] O. Kuntze) is a premier health beverage and functional food, valued for its medicinal properties and as the most consumed beverage globally [1, 2, 3, 4]. The crop is cultivated in over 48 countries across more than 4.2 million hectares, and major tea-producing countries are China, India, Sri Lanka, Japan, and Kenya [5, 6, 7, 8]. In Africa, Kenya is the leading producer, contributing about 70% of the continent's total production followed by Malawi, Tanzania, and Uganda [6, 8]. Being cultivated across diverse landscapes, tea production is a critical driver for socio-economic development and rural livelihoods, directly supporting Sustainable Development Goals (SDGs) related

to poverty reduction and employment [9, 10]. However, the global demand for tea, similar to other agricultural commodities, is increasing rapidly, driven largely by continued population expansion. The global population is projected to expand steadily over the next five to six decades, reaching an estimated peak of approximately 10.3 billion people in the mid-2080s, compared to 8.2 billion in 2024 [11]. Meanwhile, agricultural land resources are experiencing significant pressure due to demographic growth, the impacts of climate change, progressive land degradation, and accelerating urban expansion [12, 13, 14, 15]. This necessitates maximizing land resource use efficiency to sustainably meet the growing demand for tea commodities, and this can be achieved by tea investment driven by appropriately allocating land resources based on their suitability for tea cultivation.

Land suitability evaluation (LSE) which is the process of matching a crop's specific physiological requirements with the inherent characteristics of the land [16, 17, 18, 19], is a vital tool in maximizing land use efficiency for sustainable tea production. Modern multi-criteria LSE increasingly relies on Geographic Information Systems (GIS) to facilitate multi-criteria decision-making by integrating diverse spatial datasets, such as soil properties, topography, and climate [20, 16, 9, 21, 22]. In multi-criteria LSE framework, the Analytical Hierarchy Process (AHP) has emerged as a superior method for prioritizing suitability criteria [9, 23, 24, 22]. AHP effectively decomposes complex decision rules into manageable hierarchical structures, using pairwise comparisons to assign weights based on expert judgment and literature, thereby resolving conflicts between competing environmental factors [16, 9, 25, 23, 26, 27]. While numerous studies have successfully integrated GIS and AHP to map tea suitable areas [28, 1, 16, 29, 30, 31, 9, 32, 33, 34, 35, 36], their approaches possessed inherent limitations in capturing complex, non-linear relationships between variables.

Remote sensing data and machine learning (ML) models which capture complex, non-linear relationships between variables, have been widely explored and applied in agricultural land suitability evaluation especially for digital soil mapping (DSM). Among the frequently utilized ML models in agricultural land assessment include artificial neural networks (ANN), convolutional neural networks (CNN), Cubist models, gradient boosting algorithms, k-nearest neighbor (KNN), random forest (RF), Multi-Layer Perceptron (MLP), and support vector machines (SVM) [37, 38, 39, 40, 41, 42, 43]. Within this range of algorithms, the RF is often reported to deliver superior predictive performance [37, 44, 45, 46]. Its strength lies in its ensemble approach, which captures complex interactions between soil properties and environmental predictors more robustly than single-decision trees [45, 46, 36]. Moreover, Xing et al. [36] calculated priority weights in suitability evaluation for tea cultivation using extreme gradient boosting (XGBoost), logistic regression (LR), adaptive boosting (AdaBoost), gradient boosting decision tree (GBDT), Gaussian Naïve Bayes (GNB), RF, and multilayer perceptron (MLP) machine learning models, in which RF demonstrated the best performance.

The tea sector is among the major economic cash crops in prominent three East African countries (Kenya, Tanzania, and Uganda). However, in this region, the tea sector faces significant production challenges including lower yields. For instance, in Tanzania, in places such as Tarime District, yields reported by smallholders are as low as 0.23 t/ha per year [47], significantly trailing the national potential of 5 t/ha per year. Overcoming these shortfalls requires the sustainable expansion of cultivation areas; however, such expansion must be guided by LSE to avoid blind expansion into unsuitable lands. Despite this need, there remains a lack of crop-specific land suitability studies for tea in Tanzania.

By selecting Ganyange Ward in Tarime District, which is one of the potential tea-growing hubs in Tanzania, this study aims to: (i) predict key soil properties for tea cultivation using RF based on spatial soil, climate, and vegetation covariates; (ii) evaluate the relative importance of the key soil properties, topography, climate, and accessibility criteria using AHP; and (iii) develop a comprehensive land suitability map to guide tea cultivation planning in the study area. This research provides a foundational framework for digital LSE in Tanzania's tea sector that can be applied to other tea-producing regions.

## 2 Methodology

### *2.1 Study area*

The study covered Ganyange Ward in Tarime District located in Mara Region, Tanzania. The geographical location is between latitudes 9847283—9855694 S and longitudes 673079—681185 E and covers an area of 2,677.96 ha (**Fig. 1**). The altitude of the study area ranges between 1590 m to 1850 m above sea level. The area receives annual rainfall ranging from 1,177 to 1,415 mm, with a mean annual total of approximately 1,280 mm. Maximum monthly temperatures range from 25 °C to 27 °C, while minimum monthly temperatures range between 15 °C and 16 °C. The landscape comprises of undulating, rolling and plain landforms. According to the International Soil Reference and Information Centre (ISRIC) [48], the dominant soil type is Nitisols.

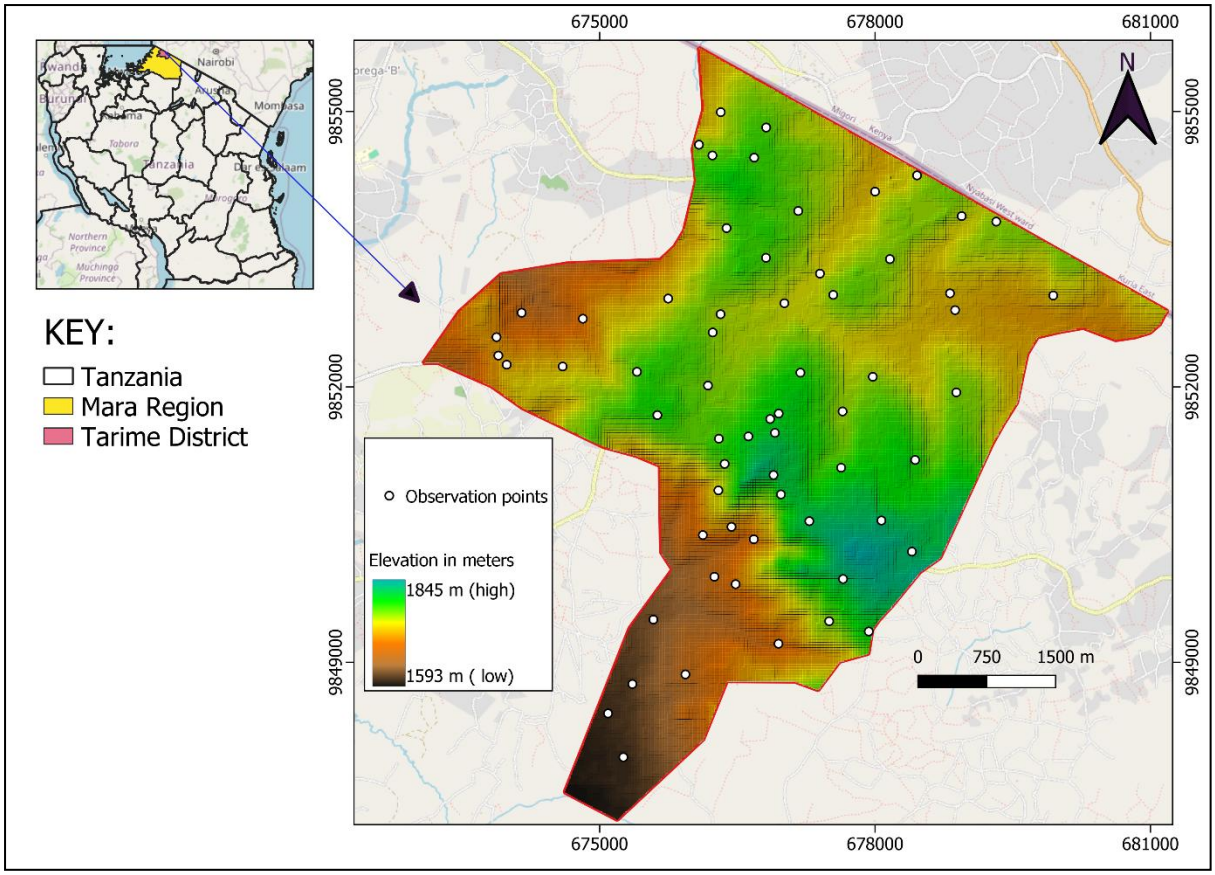



Fig. 1 Spatial distribution of observation points in the study area relative to elevation

*2.2 Soil survey and sampling procedures*

The Conditioned Latin Hypercube Sampling (cLHS) approach, following the methodology described by Brus [50], was employed to generate representative sampling locations that effectively capture the maximum soil variability across the study landscape, based on a set of environmental covariates including topographic and spectral variables. A total of 16 soil profiles were located using a handheld Global Positioning System (GPS) device and excavated to a depth of 200 cm or until a limiting layer was encountered, to expose the genetic horizons. Horizon-wise morphological properties including depth, colour, structure, texture and coarse fragments, consistence, the presence or absence of concretions, nodules, and mottles, the occurrence of cutanic coatings, and microbial activity were described following the Food and Agriculture Organization (FAO) Guidelines

for Soil Description [49]. In addition, soil samples from each genetic horizon were collected for laboratory analysis. More surface sampling locations were identified using a handheld GPS device, and 48 soil samples were collected by an auger for laboratory analysis.

*2.3 Laboratory analysis*

The collected soil samples were air-dried, passed through a 2-mm sieve, and preserved for subsequent determination of their physical and chemical characteristics. Soil particle-size distribution (**Fig. 2**) was determined using the Bouyoucos hydrometer technique [51]. Soil reaction (pH) was measured potentiometrically in a soil–water suspension prepared at a 1:2.5 ratio [52]. Electrical conductivity (EC) was measured by conductivity meter in a 1:2.5 soil: water suspension by a method described by Rhoades [58]. Cation exchange capacity (CEC) was evaluated by saturating the soil with neutral 1 M ammonium acetate ($NH_4OAc$), followed by displacement of the adsorbed $NH_4^+$ ions using 1 M potassium chloride (KCl). The displaced ammonium was then quantified through the Kjeldahl distillation procedure to estimate soil CEC [53]. Soil organic carbon content was analysed using the Walkley and Black wet oxidation method [54]. Total nitrogen was determined by the Kjeldahl digestion method as described by Bremner [59]. Available phosphorus was extracted using the Bray-I method for acidic soils [55], while the Olsen extraction method was applied for alkaline soils [56]. Exchangeable base cations were extracted with ammonium acetate, after which calcium ($Ca^{2+}$) and magnesium ($Mg^{2+}$) concentrations were measured using an atomic absorption spectrophotometer [53]. Exchangeable potassium ($K^+$) and sodium ($Na^+$) in the extract was quantified by flame photometry [57]. **Table 1** summarises laboratory results.

Table 1. Summary statistics for soil laboratory results.

| **Parameter** | **Unit** | **Min** | **Max** | **Mean** | **SD** |
|---|---|---|---|---|---|
| Soil pH | | 4.11 | 4.9 | 4.56 | 0.16 |
| EC | $dS\ m^{-1}$ | 0.02 | 0.25 | 0.11 | 0.05 |
| SOC | % | 1.03 | 5.76 | 3.55 | 0.92 |
| N | % | 0.09 | 0.27 | 0.17 | 0.03 |
| P | $mg\ kg^{-1}$ | 0.76 | 11.47 | 4.54 | 1.92 |
| $K^+$ | $cmol(+)\ kg^{-1}$ | 0.15 | 2.5 | 0.77 | 0.41 |
| $Ca^{2+}$ | $cmol(+)\ kg^{-1}$ | 0.27 | 12.28 | 7.39 | 1.59 |
| $Mg^{2+}$ | $cmol(+)\ kg^{-1}$ | 0.13 | 4.2 | 2.53 | 0.59 |
| CEC | $cmol(+)\ kg^{-1}$ | 28.56 | 79.05 | 53.14 | 8.27 |
| Sand | % | 31.6 | 72 | 50.26 | 7.89 |
| Silt | % | 14 | 43 | 23.33 | 5.75 |
| Clay | % | 10 | 42 | 26.82 | 6.13 |
| $Na^+$ | $cmol(+)\ kg^{-1}$ | 0.1 | 2.05 | 0.28 | 0.26 |

Fig. 2 Spatial distribution of soil texture classes for 0–30 cm splined data, illustrated on the United States Department of Agriculture (USDA) soil texture triangle. The positions of observations are represented by red dots. Sa (sand), LoSa (loamy sand), SaLo (sandy loam), Lo (loam), SiLo (silt loam), Si (silt), SaClLo (sandy clay loam), ClLo (clay loam), SiClLo (silty clay loam), SaCl (sandy clay), SiCl (silty clay), and Cl (clay)

*2.4 Source of data for tea cultivation suitability criteria*

Land attributes within the study area were evaluated to determine their suitability for tea cultivation using six principal criteria: (i) soil chemical properties, (ii) soil physical properties, (iii) topographic factors, (iv) climatic conditions, (v) land cover characteristics, and (vi) accessibility. These criteria were selected based on established knowledge of the agro-ecological and socio-economic requirements for tea cultivation and their relevance to land suitability evaluation frameworks. Climatic, topographic and surface cover variables were derived using the Google Earth Engine (GEE) cloud computing platform. In GEE platform, mean annual temperature and mean annual total rainfall were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset [60]. Topographic variables were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), accessed via the United States Geological Survey (USGS) EarthExplorer platform [61]; in which elevation data were processed to generate secondary topographic attributes, including slope and aspect. Land cover characteristics were accessed and processed from Sentinel-2 MultiSpectral Instrument (MSI) imagery [62], within GEE platform. These spectral data were used to compute the Normalized Difference Vegetation Index (NDVI) and to

generate land use/land cover (LULC) classifications. On the other hand, accessibility variables, including road networks and market centres, were obtained from the OpenStreetMap database [63]. These datasets were integrated into the GIS environment to assess proximity to infrastructure and market access, which influence the economic feasibility and logistical suitability of tea production.

Primary soil data were obtained from field surveys and laboratory analyses. A total of 64 soil samples were collected, comprising 16 surface-horizon samples from representative soil profile pits and 48 surface soil samples collected using an auger. From these samples, laboratory analyses were conducted to determine key soil chemical and physical properties relevant to tea growth. Soil texture was considered under the soil physical properties criterion, whereas soil chemical properties included soil pH, electrical conductivity (EC), cation exchange capacity (CEC), organic carbon (OC), total nitrogen (N), available phosphorus (P), and exchangeable base cations (K, Ca, and Mg). Descriptive statistics for these soil physical properties and chemical properties are presented in **Table 1**. The RF algorithm was subsequently employed to generate spatially continuous raster layers representing the soil suitability criteria, which were later integrated with climatic, topographic, land cover characteristics, and accessibility suitability criteria within a multi-criteria suitability framework to produce overall tea suitability map. During model prediction, laboratory results from the 64 soil samples were used for model calibration and validation, whereas remote sensing spectral indices, topographic attributes, and supplementary spatial soil information served as predictor variables. RF model outputs which demonstrated a good positive predictive power were retained for inclusion in subsequent land suitability analysis, whereas outputs with poor performance were excluded from further suitability modelling.

*2.4.1 Pre-processing of environmental covariates for RF prediction of key soil properties*

A set of environmental covariates comprising of remote sensing–derived reflectance data, Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) derived topographic variables, and kriged soil raster maps was employed in the current study **(Table 2).** Multispectral imagery from Sentinel-2A, obtained from the European Space Agency Copernicus Data Space [62], provided the primary spectral covariates, including individual bands in the blue (Band 2), green (Band 3), red (Band 4), near-infrared (NIR; Band 8), cirrus (Band 10), shortwave infrared 1 (SWIR-1; Band 11), and shortwave infrared 2 (SWIR-2; Band 12) regions. In addition to the raw spectral bands, a set of spectral indices was derived to enhance soil and vegetation characterization. These indices comprised the bare soil index (BSI), clay mineral ratio (CMR), coloration index (CI), ferrous iron index (FII), redness index (RI), coloration index (CI), grain size index (GSI), calcium-related normalized difference index (CalCI), normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), land use land cover (LULC), optimized soil adjusted vegetation index (OSAVI), and soil enhancement ratio (SER).

Table 2. Environmental covariates used as predictors for key soil properties.

| Source | Covariate data | Formula/Definition | Resolution |
|---|---|---|---|
| **Sentinel 2A** | $B2$, $B3$, $B4$, $B8$, $B10$, $B11$ & $B12$ spectral bands | $B2$ = Blue, $B3$ = Green, $B4$ = Red, $B8$= NIR –Near Infrared, $B10$= Cirrus, $B11$ = SWIR-1—Shortwave Infrared 1, and B12 = SWIR-2—Shortwave Infrared 2 | 10 m |
| | Bare Soil Index (BSI) | $BSI = \frac{(B11 + B4) - (B8 + B2)}{(B11 + B4) + (B8 + B2)}$ | 10 m |
| | Clay Mineral Ratio (CMR) | $CMR\ \frac{B11}{B12}$ | 10 m |
| | Coloration Index (CI) | CI = $\frac{B4}{B2}$ | 10 m |
| | Ferrous Iron Index (FII) | $FII = \frac{B11}{B8}$ | 10 m |

| | | | |
|---|---|---|---|
| | Grain Size Index (GSI) | $GSI\ \frac{B4 - B2}{B4 + B2 + B3}$ | 10 m |
| | Normalized Difference Calcareous Index (CalCI) | $CalCI = \frac{B11 - B12}{B11 + B2}$ | 10 m |
| | Normalized Difference Vegetation Index (NDVI) | $NDVI = \frac{B8 - B4}{B8 + B4}$ | 10 m |
| | Redness Index (RI) | $RI = \frac{B4^2}{B2\ X\ B3}$ | 10 m |
| **Source** | **Covariate data** | **Formula/Definition** | **Resolution** |
| | Soil Adjusted Vegetation Index (SAVI) | $SAVI = \frac{(B8 - B4)}{(B8 + B4 + L)}\ X\ (1 + L)$ | 10 m |

| | | | |
|---|---|---|---|
| | | where $L$ is the soil brightness correction factor (commonly $L = 0.5$) | |
| | Land Use Land Cover (LULC) | | 10 m |
| | Optimized Soil-Adjusted Vegetation Index (OSAVI) | $OSAVI = \frac{B8 - B4}{B8 + B4 + 0.16}$ | 10 m |
| | Soil Enhancement Ratio (SER) | $SER = \frac{B11}{B8}$ | 10 m |
| **DEM(SRTM)** | Elevation | | 30 m |
| | Slope | | 30 m |
| | Aspect | | 30 m |
| | Slope Length | | 30 m |
| | Topographic Wetness Index (TWI) | | 30 m |
| | Plan Curvature | | 30 m |
| | Total Curvature | | 30 m |

| | | |
|---|---|---|
| **Kriged soil maps** | Soil pH | 10 m |
| | Soil Organic Carbon (SOC) | 10 m |
| | Potassium ($K^+$) | 10 m |
| | Calcium ($Ca^{2+}$) | 10 m |
| | Magnesium ($Mg^{2+}$) | 10 m |
| | Sodium ($Na^+$) | 10 m |
| | Electrical conductivity (EC) | 10 m |
| | Cation exchange Capacity (CEC) | 10 m |
| | Silt content | 10 m |
| | Sand content | 10 m |

Topographic predictors were extracted from the USGS 30-m SRTM DEM [61], using the System for Automated Geoscientific Analyses–Geographic Information System (SAGA-GIS) processing framework. The derived topographic data included elevation, slope, aspect (As), slope-length (LS) factor, topographic wetness index (TWI), drainage, plane curvature and total curvature. In addition, Ordinary Kriging (OK)–derived ancillary soil raster layers of correlated soil properties showing strong pedological relationships with the target soil property were incorporated alongside topographic and spectral covariates as additional predictors in the modelling process. All environmental covariates were standardized to a common coordinate reference system, spatial extent, and a uniform spatial resolution of 10 m using ArcGIS 10.4 software. **Table 3** presents a summary of processed soil, topographic, and vegetation covariates used as predictors of key soil properties for tea growth in the study area.

Table 3. Summary statistics for processed soil, topography, and vegetation covariates.

| **Factor** | **Unit** | **Min** | **Max** | **Mean** | **SD** |
|---|---|---|---|---|---|
| **Soil** | | | | | |
| pH | | 4.23 | 4.72 | 4.53 | 0.10 |
| EC | $dS\ m^{-1}$ | 0.06 | 0.22 | 0.12 | 0.03 |
| SOC | % | 2.19 | 4.89 | 3.57 | 0.54 |
| N | % | 0.13 | 0.21 | 0.17 | 0.01 |
| P | $mg\ kg^{-1}$ | 2.80 | 8.74 | 4.27 | 0.89 |
| K | $cmol(+)\ kg^{-1}$ | 0.42 | 1.51 | 0.78 | 0.19 |
| Ca | $cmol(+)\ kg^{-1}$ | 4.22 | 9.31 | 7.44 | 0.92 |
| Mg | $cmol(+)\ kg^{-1}$ | 1.15 | 3.36 | 2.51 | 0.23 |

| | | | | | |
|---|---|---|---|---|---|
| CEC | *cmol(+) kg⁻¹* | 37.67 | 60.91 | 52.43 | 3.47 |
| sand | *%* | 12.18 | 62.61 | 46.14 | 6.47 |
| silt | *%* | 16.49 | 36.33 | 23.82 | 4.38 |
| Na | *cmol(+) kg⁻¹* | 0.11 | 0.70 | 0.27 | 0.11 |
| **Topography** | | | | | |
| DEM | *m* | 1593 | 1845 | 1742 | 50 |
| slope | *%* | 0.00 | 48.63 | 8.50 | 5.55 |
| aspect | *degree* | 0.02 | 360.00 | 199.46 | 106.47 |
| **Spectral data** | | | | | |
| NDVI | | 0.015 | 0.897 | 0.606 | 0.105 |
| SAVI | | 0.004 | 0.655 | 0.367 | 0.073 |
| OSAVI | | 0.006 | 0.663 | 0.411 | 0.076 |
| SER | | 0.011 | 0.421 | 0.217 | 0.045 |
| BSI | | -0.442 | 0.303 | -0.026 | 0.097 |
| CalCL | | 0.118 | 0.757 | 0.550 | 0.041 |
| CI | | -1.069 | 0.727 | 0.401 | 0.094 |
| CMR | | 1.022 | 2.456 | 1.563 | 0.153 |
| FII | | 0.926 | 3.023 | 1.617 | 0.118 |
| GSI | | -0.248 | 0.420 | 0.156 | 0.049 |
| RI | | -0.403 | 0.413 | -0.017 | 0.087 |

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### *2.4.2 Prediction of key soil properties for tea cultivation using Random Forest*

*Prediction model*

The RF is an ensemble-based machine learning technique that generates numerous decision trees to capture complex and non-linear interactions between soil properties and environmental predictors. Prior to model calibration, soil laboratory measurements were log-transformed to minimize skewness and approximate normality. Predicted values were subsequently back-transformed to their original units to facilitate spatial visualization and interpretation. The relatively weak statistical associations observed between certain soil attributes and environmental covariates likely reflect the influence of prolonged agricultural activities, which may have altered inherent soil–landscape relationships. To enhance predictive performance, soil variables exhibiting significant correlations and clear pedological relationships were incorporated as auxiliary predictors in predicting related soil properties. The RF models were parameterized using soil, climate, organisms, relief, parent material, age, and spatial position (SCORPAN)-derived environmental covariates to characterize the spatial variability of selected soil properties and to quantify the relative contribution of predictor variables, including topographic attributes, spatial coordinates, spatial soil information, and vegetation indices.

Prediction was conducted in R using the ranger package. To ensure rigorous assessment of predictive performance, spatial cross-validation was performed within the caret Applications for Spatial-Temporal Models (CAST) framework. Soil observations were structured as spatial data using geographic coordinates (x, y) referenced to an appropriate projected coordinate system. Spatial autocorrelation was accounted for through a block-based cross-validation strategy, in which the study area was partitioned

into four spatially independent folds. In each iteration, entire spatial blocks were excluded from model training and reserved for validation, thereby reducing the risk of overly optimistic accuracy estimates caused by spatial dependence. This approach resulted in approximately 75% of observations allocated for model calibration and 25% for validation per fold. Model accuracy metrics were computed across all spatial folds, and permutation-based variable importance measures were examined to identify dominant predictors influencing each soil property. Following cross-validation, a final RF model was fitted using the complete dataset and optimized hyperparameters to produce continuous, spatially explicit predictions of the target soil properties.

*Model performance evaluation*

Predictive performance was assessed through a spatial cross-validation framework to obtain an unbiased evaluation in the presence of spatial autocorrelation. Model accuracy was quantified using three complementary statistical indicators: the Root Mean Square Error (RMSE) calculated using **Eq. 1**, the Mean Absolute Error (MAE) determined using **Eq. 2**, and the Coefficient of Determination ($R^2$) calculated using **Eq. 3**. RMSE served as the principal measure of overall prediction error, reflecting the magnitude of deviations between observed and predicted values. MAE was included as a more robust metric that is comparatively less influenced by extreme residuals. The coefficient of determination ($R^2$) was used to estimate the proportion of variability in the observed soil properties accounted for by the model.

Within each spatial fold, the RF model was calibrated using spatially independent training data (approximately 75% of the total observations), while the remaining 25% of samples were reserved for validation. Performance statistics were computed for each fold

separately. Overall model accuracy was then summarized by reporting the mean and standard deviation of RMSE, MAE, and $R^2$ across all spatial folds, thereby providing a stable and reliable estimate of predictive capability under spatially structured conditions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \hat{y}i)^2}{\sum_{i=1}^{n}(yi - \bar{y})^2} \quad (3)$$

where $yi$ is the observed value, $\hat{y}i$ is the predicted value, $\bar{y}$ is the mean of observed values, and $n$ is the number of observations.

### *2.5 Ranking the suitability criteria for tea cultivation*

The Analytical Hierarchy Process (AHP), introduced by Saaty [65], serves as a structured framework for prioritization and decision-making [64]. Over time, it has gained extensive application in land evaluation, particularly in studies concerning crop suitability analysis. In the present study, soil properties, climatic, topographic, land cover characteristics, and accessibility criteria were evaluated, and corresponding weights were assigned. During this process, a pairwise comparison matrix was constructed using a predefined scale of preference levels among the considered alternatives. Based on expert judgments, local stakeholders' perceptions, and findings from the literature, the relative preference

between factors was rated on a nine-point scale (**Table 4**), where 1 denotes equal importance, 3 indicates moderate importance, 5 signifies strong importance, 7 represents very strong importance, and 9 denotes extremely strong importance over another factor. Intermediate judgments were assigned using values of 2, 4, 6, or 8. The reciprocal values (1/2 to 1/9) were used when the inverse relationship was true.

113 Table 4. The Saaty Fundamental Scale [65].

| Intensity of Importance | Definition | Explanation |
|---|---|---|
| 1 | Equal importance | Two activities contribute equally to the objective |
| 3 | Moderate importance of one over another | Experience and judgment moderately favour one activity over another |
| 5 | Essential or strong importance | Experience and judgment strongly favour one activity over another |
| 7 | Very strong importance | An activity is strongly favoured and its dominance demonstrated in practice |
| 9 | Extreme importance | The evidence favouring one activity over another is of the highest possible order of affirmation |
| 2, 4, 6, 8 | Intermediate values | Used when compromise between two judgments is needed |
| Reciprocals | If activity *i* is assigned a value when compared to *j*, then *j* gets the reciprocal when compared with *i* | |
| Rationals | Ratios arising from the scale; finer values such as 1.1, 1.2, etc., may also be used when needed | |

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115 The AHP framework also included a consistency check to evaluate the logical coherence
116 of the pairwise comparisons. This was achieved by calculating the Consistency Ratio (CR)
117 in **Eq. 4**, defined as:

$$CR = \frac{CI}{RI} \quad (4)$$

where CR is the consistency ratio, CI is the consistency index, and RI denotes the random consistency index (**Table 5**). The CI (**Eq. 5**) is computed as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (5)$$

Here, $\lambda max$ is the maximum eigenvalue and *n* is the number of criteria. All AHP pairwise comparisons in the current study ensured that the acceptable level of consistency within the pairwise comparison judgments was reached. According to AHP standards, a matrix is considered acceptably consistent when $CR \leq 0.10$.

Table 5. Random consistency index (RI) [66, 32, 16].

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RI | 0 | 0 | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 | 1.51 | 1.48 | 1.56 | 1.57 | 1.59 |

*2.6 Standardization of criteria*

Since soil properties, climatic, topographic, land cover characteristics, and accessibility raster layers were measured on different scales, they were standardized to ensure that all spatial suitability criteria were comparable on a uniform scale ranging from 0 to 1. The standardization was performed using **Eq. 6:**

$$Z = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (6)$$

where $Z$ denotes the standardized score, $X_{min}$ and $X_{max}$ represent the minimum and maximum cell values of each criterion respectively, and $X$ is the cell value of the spatial raster layer of a given criterion.

*2.7 Mapping of tea suitability*

The overall tea suitability map was generated by integrating all standardized criteria using a weighted sum overlay analysis (**Eq. 7**), implemented in the R programming environment.

$$V_i = \sum_{i=1}^{n} (w_i \ X \ u_i) \quad (7)$$

*Vi* denotes land suitability score, *w* represents the weight of the ith criterion, *u* denotes the standardized score value of the i$^{th}$ criterion, and *n* is the total number of criteria (*i* = 1, 2, 3, …, *n*).

The overall suitability raster was then reclassified into four classes of equal ranges according to the land suitability classification of FAO [67] as tabulated in **Table 6**. The tea suitability classes included the highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (N) classes with 4, 3, 2, and 1 class values, respectively.

Table 6. Suitability classification [67].

| Suitability class | Symbol | Rating | Raster Value |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Highly suitable | S1 | 0.75 – 1.00 | 4 |
| Moderately suitable | S2 | 0.50 – 0.75 | 3 |
| Marginally suitable | S3 | 0.25 – 0.50 | 2 |
| Not suitable | N | 0 – 0.25 | 1 |

*2.8 Agro-ecological suitability thresholds for tea cultivation reported in the literature*

A comprehensive review of relevant literature was undertaken to harmonize agro-ecological suitability thresholds for tea cultivation and to establish a robust baseline framework for interpreting the suitability results of the present study. Suitability thresholds were categorized into four classes—Highly suitable (S1), Moderately suitable (S2), Marginally suitable (S3), and Not suitable (N), and assigned numerical scores of 4, 3, 2, and 1, respectively (**Table 7**). Sources for classification ratings were; soil chemical and physical properties [28, 1, 29, 32, 34, 36], topography [28, 1, 29, 32, 34, 36], climate [28, 1, 29, 68, 32, 34, 36], land cover characteristics [28, 1, 29, 34], and accessibility [29, 34].

Table 4. Harmonized agro-ecological suitability thresholds for tea cultivation reported in the literature.

| **Factor** | **Criteria** | **Unit** | **Highly Suitable** | **Moderately Suitably** | **Marginally Suitable** | **Not Suitable** |
|---|---|---|---|---|---|---|
| | | Symbol | **S1** | **S2** | **S3** | **N** |
| | | Class Value | **4** | **3** | **2** | **1** |
| **Soil** | Soil pH | | 4.5 – 5.5 | 5.6 – 6.0, 4.4 – 4.0 | 6.1 – 7.0, <4.0 | >7.0 |
| | EC | *dS m⁻¹* | < 0.9 | 0.9 – 1 | 1 – 2 | > 2 |
| | SOC | *%* | > 7 | 4–7 | 3–4 | <3 |
| | P | *mg kg⁻¹* | > 10 | 5 – 10 | 3 – 5 | < 3 |
| | $K^+$ | *cmol(+) kg⁻¹* | > 0.6 | 0.3 – 0.6 | 0.2 – 0.3 | < 0.2 |
| | Soil texture | | Loam | Clay loam | Sandy loam | Sandy, clay |
| **Topography** | Elevation | *m* | 1000 – 2500 | 600 – 1000 | 2500 – 3000, 300 – 600 | < 300, > 3000 |
| | Slope | *%* | < 13 | 13 –25 | 25 – 55 | >55 |
| | Aspect | *degree (◦)* | 0 – 67.5, 292.5 – 337.5 | 67.5–112.5 ,247.5 – 292.5 | 112.5 – 157.5, 202.5 - 247.5 | 157.5 – 202.5 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Climate** | Rainfall | *mm* | 1200 – 2500 | 800 – 1200 | 600 – 800 | < 600 |
| | Temperature | ◦*C* | 18-25 | 26-28, 15-17 | 29-30, 13-14 | >30, <13 |
| **Land cover x-tics** | NDVI | | >0.6 | 0.4 - 0.6 | 0-0.4 | <0 |
| | LULC | | Forest/tea plantation | Shrubland | Cropland/ grassland | Bare/built-up areas |
| **Accessibility** | Roads | *km* | 0–1 | 1 – 2 | 2 – 4 | >4 |
| | Market centres | *km* | 0 - 2.2 | 2.2 - 3.8 | 3.8 - 8 | >8 |

## 3 Results and discussion

### *3.1 Prediction of soil properties using Random Forest*

Key soil properties in the selected tea-potential area were predicted using a RF machine-learning approach within a DSM framework, integrating SCORPAN-based environmental covariates, including DEM-derived topographic variables, Sentinel-2A spectral indices, and spatial soil information. Model performance **(Table 8)** for properties with positive predictive power, expressed as coefficient of determination ($R^2$), ranged from 36.4% to 78.7%. The RF model most accurately predicted electrical conductivity (EC) ($R^2$ =78.7%, RMSE = 0.019 dS $m^{-1}$, MAE = 0.013 dS $m^{-1}$), which is highly sensitive to soil texture and moisture status. This was followed by silt content ($R^2$ =67.1%, RMSE = 0.124%, MAE = 0.090%), likely reflecting its strong linkage with topographic redistribution and moisture dynamics effectively captured by topographic variables. Soil reaction (pH) also showed good accuracy ($R^2$ =57.4%, RMSE = 0.018, MAE = 0.018), indicating that the model successfully represented texture-mediated buffering and topography-controlled leaching processes.

Prediction of exchangeable K ($R^2$ = 49.0%, RMSE = 0.135 cmol(+) $kg^{-1}$, MAE = 0.095 cmol (+) $kg^{-1}$), soil organic carbon (SOC) ($R^2$ = 44.7%, RMSE = 0.155%, MAE = 0.101%) and available phosphorus (P) ($R^2$ =40.9%, RMSE = 0.257 $mgkg^{-1}$, MAE = 0.188 $mgkg^{-1}$) demonstrated moderate performance, reflecting pronounced small-scale variability driven by intensive cultivation and localized management practices such as fertilizer and manure application. Clay content ($R^2$ = 0.364, RMSE = 0.197%, MAE = 0.132%) recorded the lowest positive accuracies, attributed to complex mineralogical variability, respectively.

Table 5. Performance of Random Forest prediction for studied soil properties predicted with positive power.

| **Soil property** | Metrics of prediction accuracy | | | | Standard deviations of the metrics | | |
|---|---|---|---|---|---|---|---|
| | **Unit** | **RMSE** | **MAE** | **$R^2$** | **RMSE - SD** | **MAE - SD** | **$R^2$ - SD** |
| silt | *%* | 0.124 | 0.090 | 0.671 | 0.015 | 0.008 | 0.058 |
| EC | *$dS\ m^{-1}$* | 0.019 | 0.013 | 0.787 | 0.006 | 0.004 | 0.077 |
| pH | | 0.018 | 0.012 | 0.574 | 0.009 | 0.005 | 0.268 |
| P | *$mg\ kg^{-1}$* | 0.257 | 0.188 | 0.409 | 0.116 | 0.075 | 0.197 |
| SOC | *%* | 0.155 | 0.101 | 0.447 | 0.044 | 0.022 | 0.179 |
| K | *$cmol(+)\ kg^{-1}$* | 0.135 | 0.095 | 0.490 | 0.026 | 0.013 | 0.099 |
| clay | *%* | 0.197 | 0.132 | 0.364 | 0.066 | 0.033 | 0.231 |

pH=soil pH, EC=electrical conductivity, P = available phosphorus, SOC = soil organic carbon, K = exchangeable potassium, RMSE=Root Mean Square Error; MAE=Mean Absolute Error; $R^2$=Coefficient of Determination; SD=Standard Deviation

*3.2 Relative priority weights of criteria for tea suitability*

The comparison matrix, relative priority weights (PW), and Consistency Ratio (CR) derived from expert judgments for tea land suitability factors are presented in **Table 9**. The overall CR values (< 0.10) across all comparison levels indicate acceptable consistency in the AHP judgments [64], confirming the reliability of the assigned weights. At the highest hierarchical level, climate emerged as the most influential factor (PW = 0.37), followed by soil chemical properties (PW = 0.25), soil physical properties (PW = 0.18), topography (PW = 0.12), land cover characteristics (PW = 0.05), and accessibility (PW = 0.03). The dominance of climate reflects tea's high sensitivity to rainfall distribution and temperature regimes [69, 70, 71]. Tea (*Camellia sinensis*) is a perennial crop whose productivity and leaf quality are strongly controlled by hydrothermal conditions. Adequate and well-distributed rainfall sustains continuous vegetative flushing, while moderate temperatures regulate physiological processes such as photosynthesis and transpiration [72]. Within the climate factor, rainfall (PW = 0.67) ranked substantially higher than temperature (0.33), underscoring the critical importance of sufficient soil moisture supply for optimal tea growth. Although temperature influences growth rates and quality attributes [73], rainfall directly governs soil moisture availability, nutrient mobility, and overall biomass production.

Among soil chemical properties, soil pH (PW = 0.48) was identified as the most influential criterion, followed by SOC (PW = 0.26), available P (PW = 0.14), K (PW = 0.07), and EC (PW = 0.05). Soil pH is widely recognized as a master variable controlling nutrient solubility, microbial activity, and cation availability. Tea thrives best under moderately acidic conditions, and slight deviations from the optimal pH range can substantially reduce nutrient uptake efficiency [29, 68, 34]. The high ranking of SOC reflects its role in

improving soil structure, moisture retention, and nutrient buffering capacity—critical for sustained tea productivity under tropical conditions. For soil physical properties, silt (PW = 0.67) was weighted higher than clay (PW = 0.33). This prioritization reflects the importance of balanced soil texture in regulating drainage and aeration. Tea requires well-drained yet moisture-retentive soils; excessive clay may induce poor drainage and root stress, while appropriate silt content enhances water-holding capacity without causing waterlogging.

In assessing topography, elevation (PW = 0.57) ranked above slope (PW = 0.33) and aspect (PW = 0.10). Elevation significantly influences microclimatic conditions, particularly temperature gradients that affect tea quality and growth cycles. While slope affects erosion risk and mechanization feasibility, and aspect modifies solar radiation exposure, elevation exerts a broader climatic control, justifying its higher priority. For land cover characteristics, NDVI (PW = 0.75) was more influential than LULC (PW = 0.25). NDVI directly reflects vegetation vigour and canopy health, serving as a proxy for biomass productivity and microclimatic buffering—both essential for tea plantations. LULC provides contextual land-use information but has a more indirect influence on crop performance. Finally, in accessing accessibility, proximity to roads (PW = 0.80) was ranked higher than proximity to marketing centres (PW = 0.20). Tea is a highly perishable crop that requires rapid transport to processing facilities to maintain leaf quality, thus, road access is critical for minimizing post-harvest losses and ensuring economic viability. Overall, the priority structure reflects the eco-physiological requirements of tea cultivation, where hydrothermal conditions and soil fertility dominate suitability decisions, while infrastructural and land-cover factors play supportive yet comparatively lesser roles.

Table 6. Comparison matrix and relative priority weights (PW) for tea land suitability factors and their criteria.

| **Factor** | **Criteria** | **Pairwise comparison matrix scores** | | | | | **PW** | **CR** |
|---|---|---|---|---|---|---|---|---|
| **Soil** | **Chemical properties** | *pH* | *SOC* | *P* | *K* | *EC* | | |
| | *pH* | 1 | 2 | 5 | 7 | 8 | 0.48 | 0.071 |
| | *SOC* | 0.5 | 1 | 2 | 5 | 6 | 0.26 | |
| | *P* | 0.2 | 0.5 | 1 | 3 | 4 | 0.14 | |
| | *K* | 0.14 | 0.2 | 0.33 | 1 | 3 | 0.07 | |
| | *EC* | 0.13 | 0.17 | 0.25 | 0.33 | 1 | 0.05 | |
| | **Physical properties** | *Silt* | *Clay* | | | | | |
| | *Silt* | 1 | 2 | | | | 0.67 | 0.000 |
| | *Clay* | 0.5 | 1 | | | | 0.33 | |
| **Topography** | **Topographic criteria** | *Elevation* | *Slope* | *aspect* | | | | |
| | *Elevation* | 1 | 2 | 5 | | | 0.57 | 0.035 |
| | *Slope* | 0.50 | 1 | 4 | | | 0.33 | |
| | *aspect* | 0.20 | 0.25 | 1 | | | 0.10 | |
| **Climate** | **Climatic criteria** | *RAIN* | *TEMP* | | | | | |
| | *Rainfall (RAIN)* | 1 | 2 | | | | 0.67 | 0.000 |

| | | | | | |
|---|---|---|---|---|---|
| | *Temperature (TEMP)* | 0.3 | 1 | 0.33 | |
| **Land cover** | **Land cover criteria** | *NDVI* | *LULC* | | |
| | *NDVI* | 1 | 3 | 0.75 | 0.000 |
| | *LULC* | 0.3 | 1 | 0.25 | |
| **Accessibility** | **Accessibility criteria** | *R* | *M* | | |
| | *Proximity to Roads (R)* | 1 | 4 | 0.80 | 0.000 |
| | *Proximity to Marketing centres (M)* | 0.3 | 1 | 0.20 | |

| **Land suitability factors** | Climate | Soil chemical... | Soil physical… | Topography | Land cover… | Accessibility | | |
|---|---|---|---|---|---|---|---|---|
| Climate | 1 | 2 | 3 | 3 | 6 | 8 | 0.37 | 0.074 |
| Soil chemical properties | 0.5 | 1 | 2 | 3 | 5 | 7 | 0.25 | |
| Soil physical properties | 0.33 | 0.5 | 1 | 3 | 4 | 6 | 0.18 | |
| Topography | 0.2 | 0.5 | 0.33 | 1 | 3 | 5 | 0.12 | |
| Land cover characteristics | 0.14 | 0.2 | 0.25 | 0.33 | 1 | 3 | 0.05 | |
| Accessibility | 0.13 | 0.17 | 0.17 | 0.25 | 0.33 | 1 | 0.03 | |

Key: PW = priority score, CR = consistency ratio

*3.3 Suitability for tea cultivation based on soil chemical properties*

The suitability map showing spatial distribution of soil chemical suitability for tea cultivation is presented by **Fig. 3**. The results in **Table 10** indicate that only 0.003% of the area is highly suitable (S1), whereas 25.37% is moderately suitable (S2), 56.83% is marginally suitable (S3), and 17.80% is not suitable (N) for tea cultivation. The predominance of marginally suitable soils reflects inherent chemical limitations that constrain optimal tea growth and yield potential. Pairwise comparison matrix showed that soil pH was the most influential chemical criterion, followed by SOC, available P, K, and EC. The pH condition of the study area is agronomically justified, as tea (*Camellia sinensis*) performs best under acidic conditions (pH 4.5–5.5) [28, 1, 29, 68, 34, 36]**.** In the study area, soil pH ranged from 4.23 to 4.72 (**Table 3**), placing most soils within the S1 range based on literature ratings. This indicates that pH does not constitute a major limiting factor and aligns with the crop's physiological preference for acidic environments. Despite favourable pH, other chemical properties reduced overall soil chemical suitability. SOC ranged from 2.19–4.89% (**Table 3**), which corresponds largely to the S3 class (3–4%), with only portions approaching moderate suitability (4–7%). Given SOC's strong influence on nutrient retention [74], aggregate stability, and moisture regulation, its moderate levels likely contributed to the dominance of marginally suitable areas.

Table 7. Percentage of areas suitable for tea cultivation based on soil chemical properties.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 0.09 | 0.003 |

| | | | | |
|---|---|---|---|---|
| Moderately suitable | 3 | S2 | 679.21 | 25.37 |
| Marginally suitable | 2 | S3 | 1521.59 | 56.83 |
| Not suitable | 1 | N | 476.71 | 17.80 |

Available phosphorus ranged from 2.80–8.74 mg $kg^{-1}$(**Table 3**) which places much of the area within marginal (3–5 $mgkg^{-1}$) to moderate suitability (5–10 $mgkg^{-1}$) classes, indicating P deficiency as a key limiting nutrient. Considering tea's high P demand for root development and shoot growth [72], suboptimal P levels significantly influenced suitability outcomes, consistent with its intermediate priority weight (PW = 0.14) during priority weighting. Exchangeable potassium showed relatively favourable values (0.42–1.51 cmol (+) $kg^{-1}$ (**Table 3**), largely falling within the highly suitable (>0.6) class. However, its lower priority weight (PW = 0.07) during priority weighting indicates that although potassium availability is generally adequate, its spatial variability exerts less influence compared to pH and SOC.

Electrical conductivity (EC) ranged from 0.06–0.22 dS $m^{-1}$, well within the highly suitable (<0.9 dS $m^{-1}$) threshold, confirming the absence of salinity constraints. However, its minimal priority weight (PW = 0.05) reflects the limited variability and negligible salinity risk in this humid highland environment. Overall, while intrinsic soil acidity strongly favours tea cultivation, moderate SOC and suboptimal phosphorus levels substantially lowered composite soil chemical suitability, resulting in the predominance of marginally suitable areas. These findings suggest that strategic soil fertility management particularly organic matter enhancement and phosphorus supplementation would significantly upgrade observed soil chemical suitability classes and improve tea productivity in the study area.

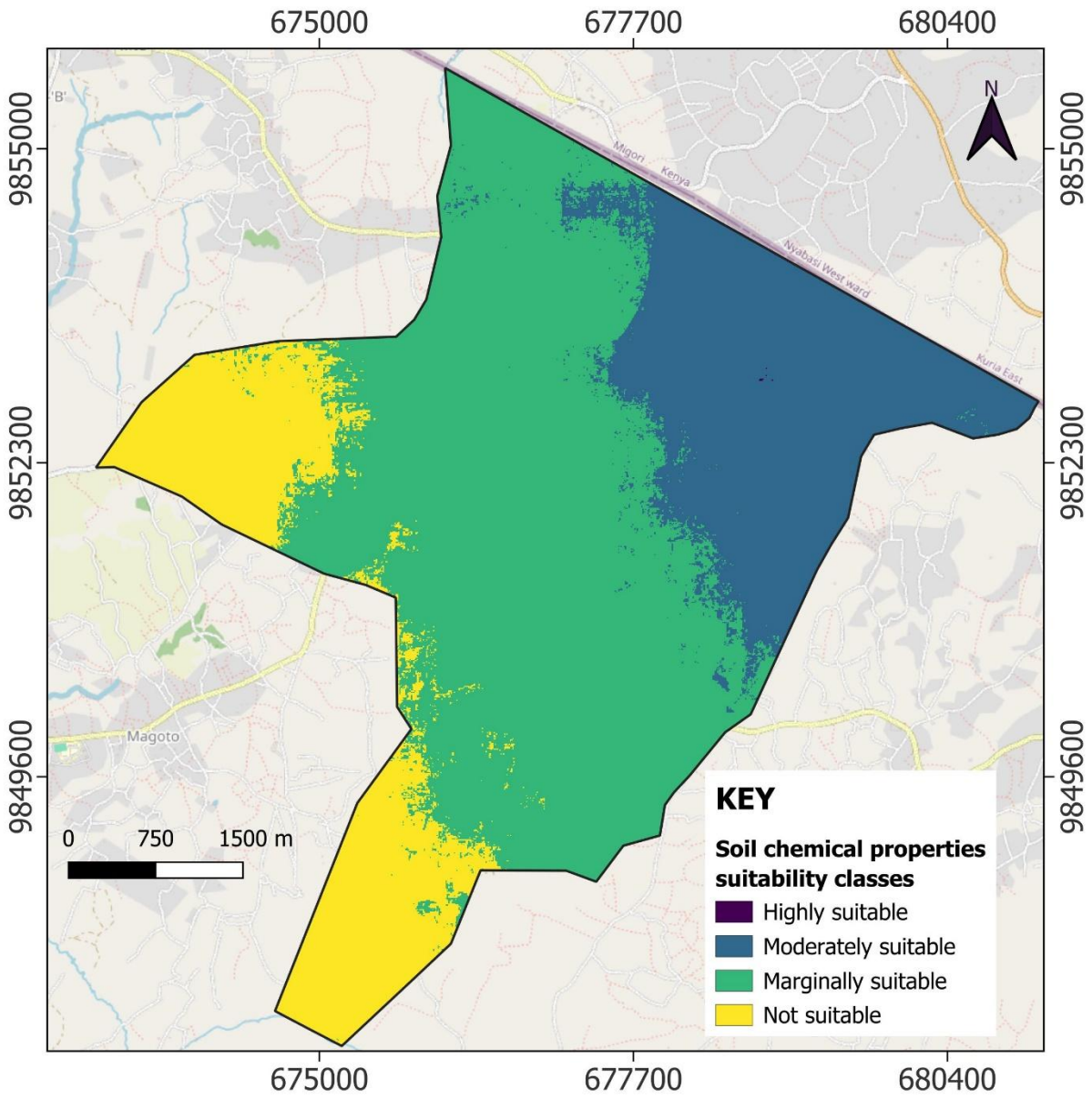



Fig. 3 Tea cultivation suitability map based on soil chemical properties

*3.4 Suitability for tea cultivation based on soil physical properties*

The suitability map for soil physical properties regarding tea cultivation is presented by **Fig. 4**. The results in **Table 11** show that 5.65% of the area is highly suitable (S1), 18.93% is moderately suitable (S2), 53.30% is marginally suitable (S3), and 22.12% is not suitable (N). The predominance of marginally suitable and non-suitable classes indicates that

physical soil constraints constitute a major limitation to optimal tea establishment in the study area. Silt (PW = 0.67) exerted greater influence than clay (PW = 0.33) in determining physical suitability during priority weighting. This prioritization reflects the importance of balanced texture for tea, which requires well-drained, friable soils with adequate moisture retention but without excessive compaction [28, 75, 74].

Table 8. Percentage of areas suitable for tea cultivation based on soil physical properties.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 151.25 | 5.65 |
| Moderately suitable | 3 | S2 | 506.92 | 18.93 |
| Marginally suitable | 2 | S3 | 1427.04 | 53.30 |
| Not suitable | 1 | N | 592.39 | 22.12 |

The observed silt content ranged from 16.49% to 36.33% (**Table 3**). This range shows that much of the area falls within the marginally suitable and not suitable textural categories, explaining the extensive S3 and N spatial coverage. Insufficient silt fractions may reduce aggregate stability and water-holding capacity, increasing susceptibility to drought stress an important consideration for perennial crops such as tea. Furthermore, the dominance of sandy textures (46.14%—62.61% range) suggests a relatively coarse-textured environment. Excessively sandy soils may promote rapid drainage and nutrient leaching. Additionally, localized higher clay proportions would fall into the non-suitable category due to poor aeration and potential waterlogging. The moderate clay influence (PW= 0.33) during priority weighting indicates that although extreme clay conditions are less widespread than silt-related constraints they still contribute to suitability differentiation.

Overall, the physical suitability pattern reflects a landscape dominated by moderately coarse-textured soils with variable silt content. Although such soils favour drainage which is an essential requirement for tea, they may limit moisture retention and structural stability without adequate organic matter management. The relatively small proportion of highly suitable areas suggests that improving soil structure through organic amendments, mulching, and conservation practices could enhance aggregate stability and upgrade marginal areas to higher suitability classes.

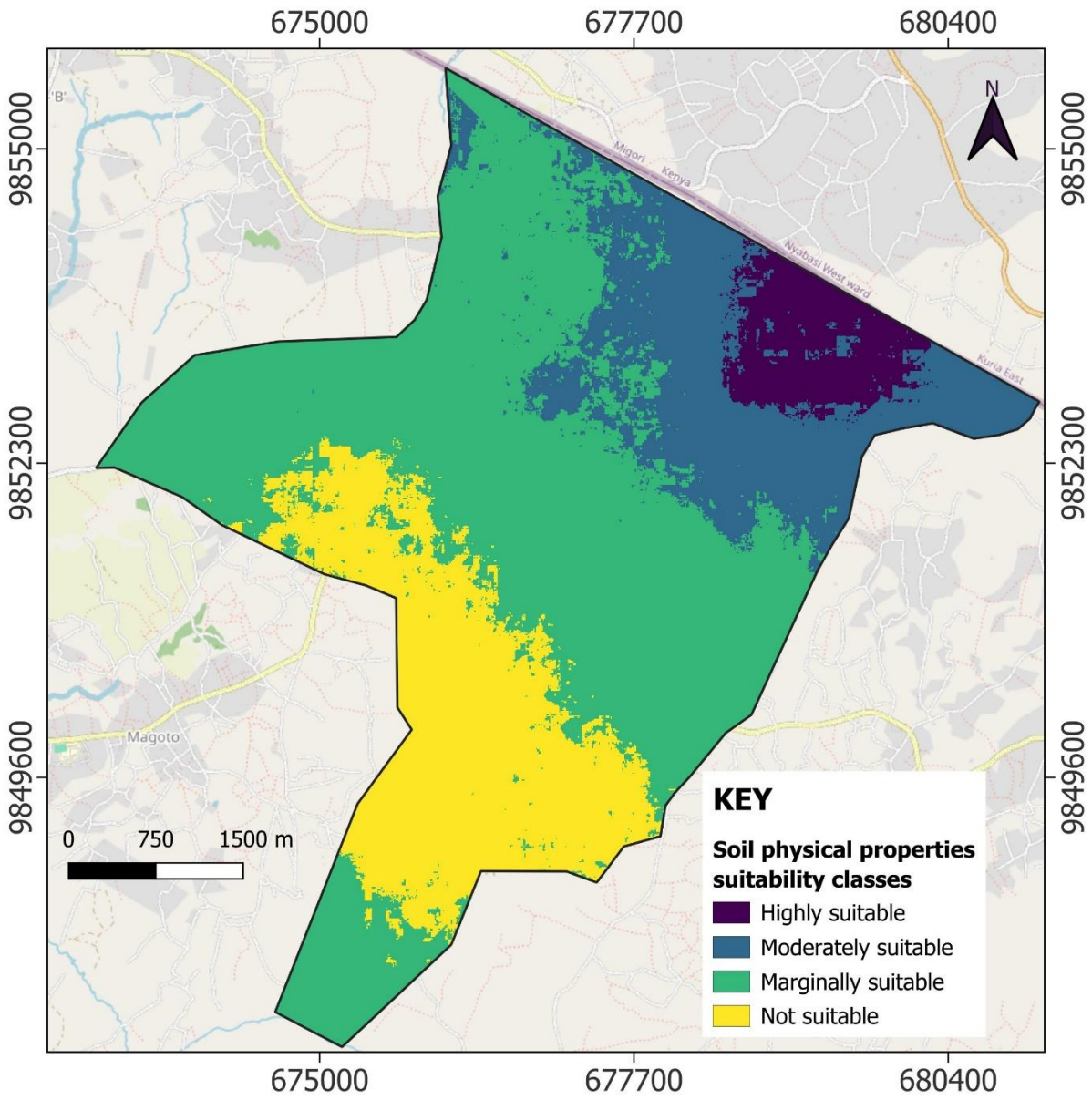



Fig. 4 Tea cultivation suitability map based on soil physical properties

*3.5 Climate suitability for tea cultivation*

**Fig. 5** presents the suitability map showing the spatial distribution of climate suitability for tea cultivation. The results in **Table 12** indicate that 43.65% of the area is moderately suitable (S2), 56.35% is marginally suitable (S3), while only 0.004% is not suitable (N). Notably, no area was classified as highly suitable (S1) under the composite climatic

evaluation. The absence of S1 reflects slight deviations from optimal rainfall thresholds rather than severe climatic limitations.

Table 9. Percentage of areas suitable for tea cultivation based on climate.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 0 | 0.00 |
| Moderately suitable | 3 | S2 | 1168.78 | 43.65 |
| Marginally suitable | 2 | S3 | 1508.70 | 56.35 |
| Not suitable | 1 | N | 0.12 | 0.004 |

Observed annual rainfall in the study area ranged from 1501 to 1551 mm (**Table 3**) indicating that the entire area almost falls within the S2 class [29, 68]. Although rainfall is adequate for sustaining tea growth, it does not reach the optimal high-yield range (>1800 mm), which explains the absence of S1 classification. The relatively low standard deviation indicates limited spatial variability, suggesting that rainfall exerts a uniform moderating effect across the landscape within the spatial coverage of the study area. Mean annual temperature ranged from 19.74 to 21.13°C, which lies squarely within the highly suitable—S1(18–25°C) class for tea [1, 29, 68, 34]. These cool highland conditions favour steady vegetative growth and high-quality leaf production. The narrow

temperature variability further confirms climatic stability within the geographical coverage of the study area, minimizing heat stress risk.

Overall, while thermal conditions are optimal for tea cultivation, rainfall levels though sufficient, remain slightly below the highly suitable threshold, resulting in dominance of moderate and marginal suitability classes. The S3 areas likely reflect micro-spatial climatic interactions or composite weighting effects rather than critical climatic stress. These findings suggest that supplemental moisture conservation strategies, such as mulching and shade management, could enhance effective water availability and potentially elevate moderate areas toward higher climatic suitability for sustainable tea production.

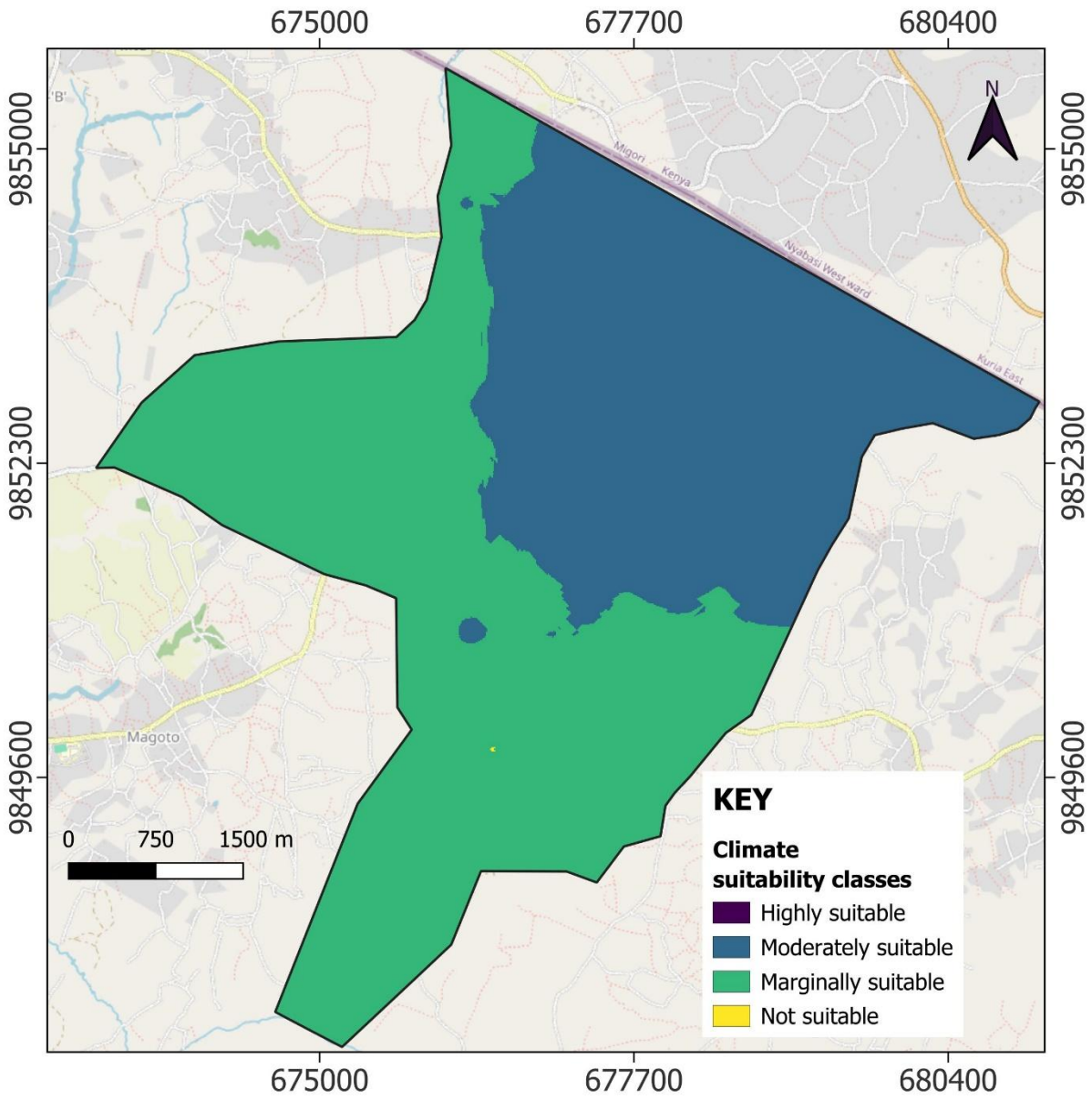



Fig. 5 Tea cultivation suitability map based on climate

*3.6 Topography suitability*

The spatial distribution of topographic suitability for tea cultivation in the study area is presented in **Fig. 6**. The results in **Table 13** indicate that 0.17% of the area is highly suitable (S1), 26.03% is moderately suitable (S2), 64.57% is marginally suitable (S3), and 9.24% is not suitable (N) topography suitability classes. The predominance of marginally suitable areas suggests that terrain conditions represent a significant limitation to optimal tea cultivation in the study area.

Table 10. Percentage of areas suitable for tea cultivation based on topography.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 4.53 | 0.17 |
| Moderately suitable | 3 | S2 | 696.86 | 26.03 |
| Marginally suitable | 2 | S3 | 1728.80 | 64.57 |
| Not suitable | 1 | N | 247.41 | 9.24 |

During pairwise comparison matrix, elevation (PW = 0.57) was identified as the most influential topographic criterion, followed by slope (PW = 0.33) and aspect (PW = 0.10). The higher weight assigned to elevation reflects its strong control over temperature regimes, moisture availability, and overall agro-climatic conditions that influence tea growth. As presented in **Table 3**, the study area is located at elevations ranging from 1593 to 1845 m above sea level (mean = 1742 m), which falls within the highly suitable range (1000–2500 m) for tea cultivation. Such highland conditions generally favour cool temperatures and prolonged vegetative growth, which enhance both yield and leaf

quality. However, despite favourable elevation conditions, only a very small portion of the landscape was classified as highly suitable under the composite topographic assessment.

Slope emerged as an important limiting factor. Results in **Table 3**, showed that the study area slope gradient ranged from 0 to 48.63% (mean = 8.50%), indicating considerable spatial variability in terrain steepness. According to the suitability thresholds presented in **Table 7**, much of the landscape falls within the moderately suitable to marginally suitable slope classes, with steeper slopes contributing to erosion risk, soil instability, and increased management difficulty for plantation establishment. These conditions likely explain the dominance of the S3 category. Aspect showed the lowest influence among the topographic factors during priority weighting and observed aspect values in **Table 3** ranged from 0° to 360° (mean = 199.46°), indicating diverse slope orientations across the study area. Aspect influences solar radiation exposure and microclimatic conditions, which can affect evapotranspiration and moisture retention. However, its relatively low priority score suggests that aspect variability exerts a smaller influence on overall tea suitability compared with elevation and slope on the study area landscape.

Overall, although the elevation of the study area provides favourable highland conditions for tea cultivation, terrain steepness significantly reduces topographic suitability in many locations. The dominance of marginally suitable areas highlights the need for appropriate land management practices, such as contour planting, terracing, and soil conservation measures, to mitigate erosion risks and improve the feasibility of tea cultivation on sloping terrain.

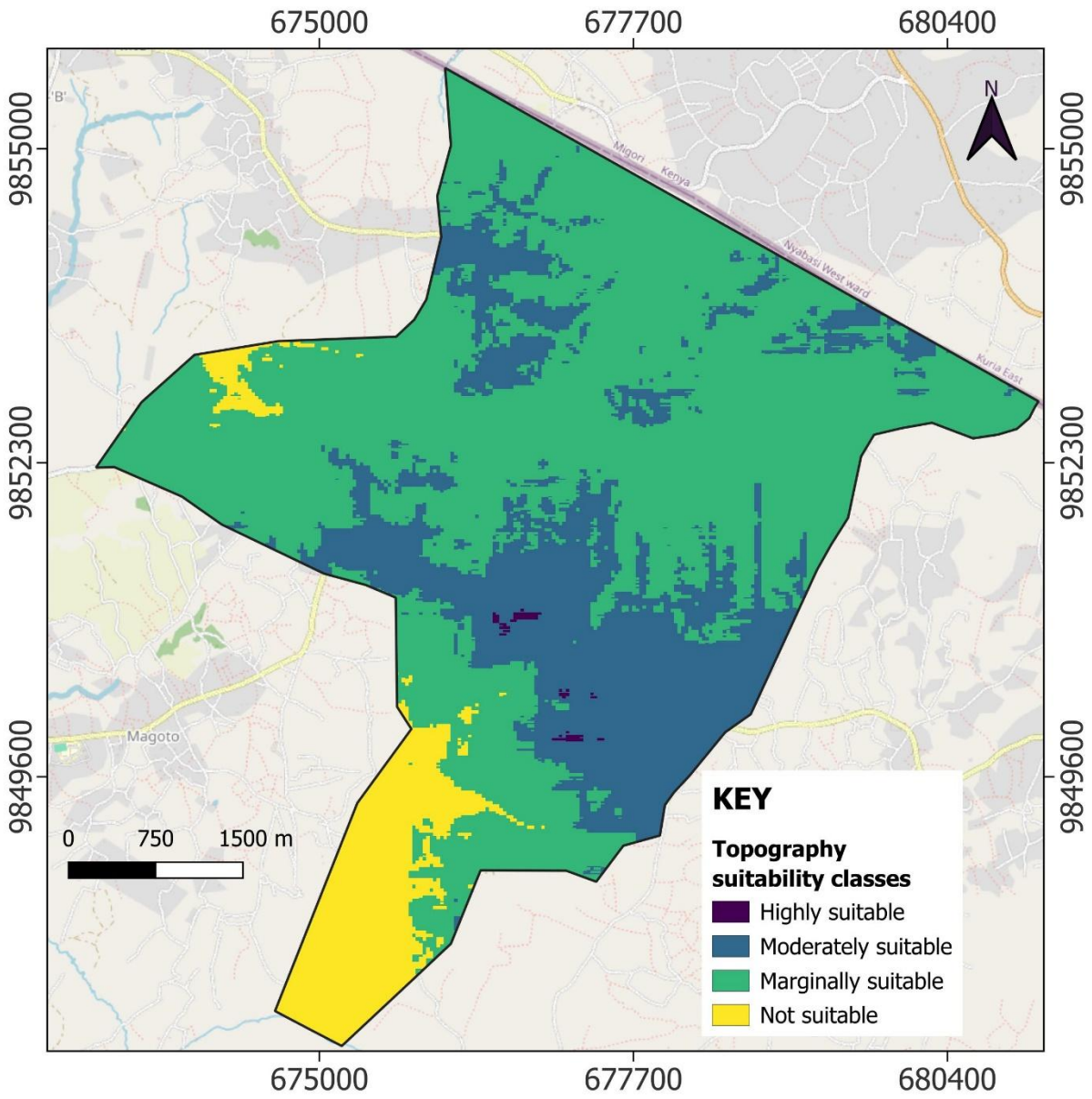



Fig. 6 Tea cultivation suitability map based on topography

*3.7 Suitability for tea cultivation based on land cover characteristics*

The spatial distribution of land cover suitability for tea cultivation is presented in **Fig. 7**. The results in **Table 14** show that 19.34% of the area is highly suitable (S1), 65.02% is moderately suitable (S2), 15.13% is marginally suitable (S3), and only 0.51% is not suitable (N). The dominance of moderately suitable areas reflects a landscape largely characterized by favourable vegetative conditions, though not entirely covered by optimal

land-use types for tea establishment. During pairwise comparison matrix, NDVI (PW = 0.75) was assigned greater importance than LULC (PW= 0.25). This prioritization highlights the strong role of vegetation vigour and biomass density in determining tea suitability, as NDVI directly reflects canopy health, photosynthetic activity, and microclimatic buffering capacity [76].

Table 11. Percentage of areas suitable for tea cultivation based on land cover characteristics.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 517.95 | 19.34 |
| Moderately suitable | 3 | S2 | 1740.84 | 65.02 |
| Marginally suitable | 2 | S3 | 405.17 | 15.13 |
| Not suitable | 1 | N | 13.63 | 0.51 |

The observed NDVI ranged from 0.015 to 0.897 (mean = 0.606) (**Table 3**), and literature's suitability thresholds show that this mean NDVI falls within S1 class [29]. However, spatial variability (SD = 0.105) indicates that substantial portions of the area fall within the moderately suitable (0.4–0.6) range, explaining the predominance of S2 in the final classification. High NDVI values correspond to dense forest cover and established tea plantations, which provide favourable microclimatic conditions such as moderated temperature, reduced evapotranspiration, and improved soil moisture retention. [32, 76, 77]. Land Use/Land Cover (LULC) further indicates suitability. Areas classified as forest or existing tea plantations indicate highly suitable conditions, whereas shrubland

corresponds to moderate suitability, and cropland/grassland to marginal suitability. Bare or built-up areas could indicate areas not suitable for tea cultivation. The very small proportion of non-suitable land (0.51%) reflects limited urbanization and/or exposed surfaces within the study area.

Overall, the land cover suitability pattern demonstrates that vegetative conditions are generally favourable for tea cultivation, with strong canopy presence and limited degraded land. The moderate dominance suggests that while vegetation vigour is adequate, expansion of tea plantations into shrubland or moderately vegetated cropland would require land-use conversion and management interventions. Enhancing vegetative cover through agroforestry integration and conservation practices could further improve suitability and sustain long-term tea productivity.

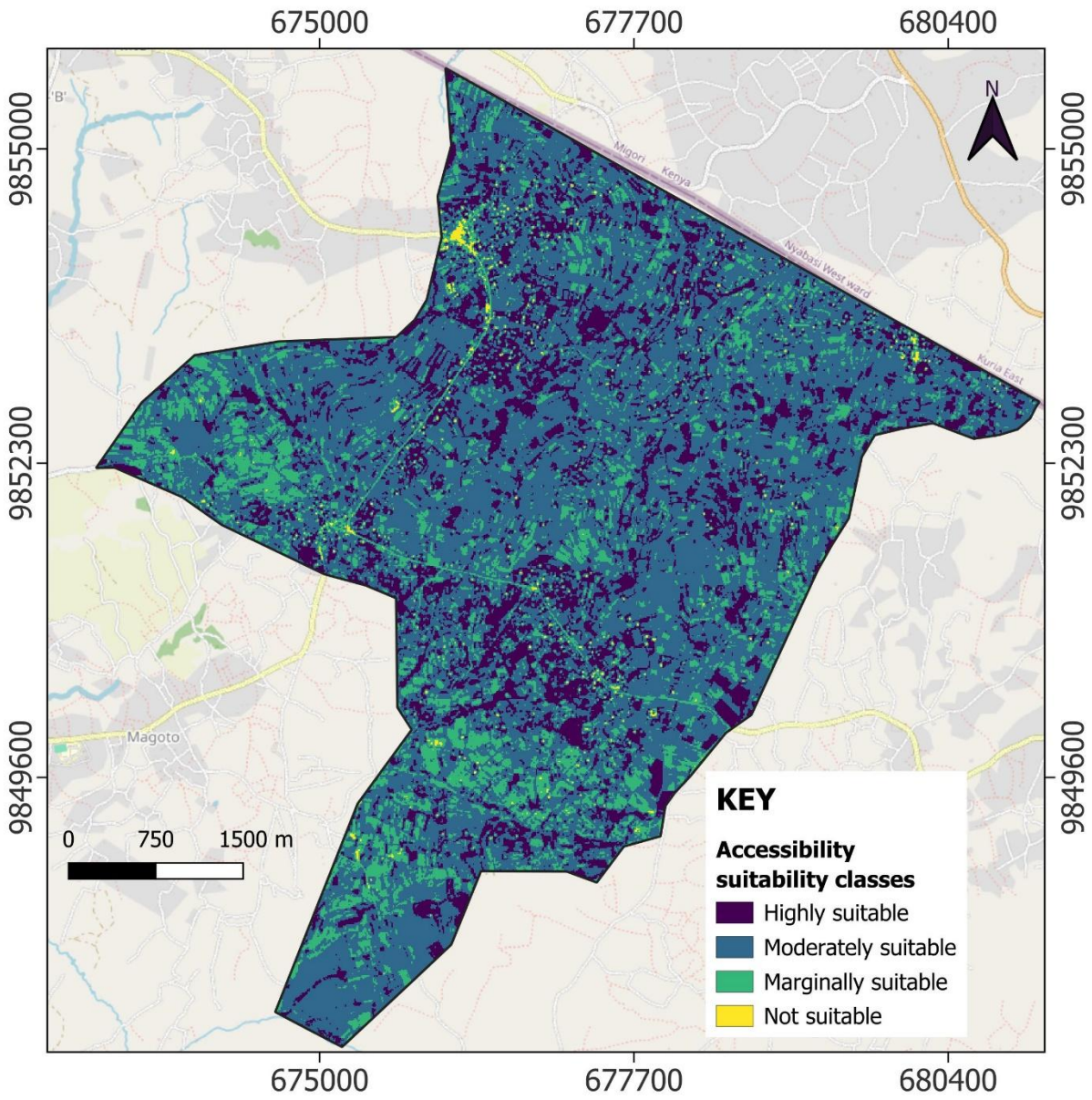



Fig. 7 Tea cultivation suitability map based on land cover characteristics

*3.8 Suitability for tea cultivation based on accessibility factors*

The spatial distribution map of accessibility suitability is presented by **Fig. 8**. The results in **Table 15** indicate that 55.08% of the area is highly suitable (S1), 33.41% is moderately suitable (S2), 10.63% is marginally suitable (S3), and only 0.87% is not suitable (N). The predominance of highly suitable areas reflects favourable infrastructure conditions that support efficient transportation of tea inputs and green leaf to processing facilities.

Pairwise comparison matrix (**Table 9**) demonstrated that proximity to roads (PW = 0.80) was considered more influential than proximity to market centres (PW = 0.20). This weighting is agronomically and economically justified, as tea is a highly perishable crop requiring rapid transport after plucking to maintain quality [78]. Road accessibility directly affects production costs, timeliness of leaf delivery, and overall profitability.

Table 12. Percentage of areas suitable for tea cultivation based on accessibility.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 1474.90 | 55.08 |
| Moderately suitable | 3 | S2 | 894.57 | 33.41 |
| Marginally suitable | 2 | S3 | 284.71 | 10.63 |
| Not suitable | 1 | N | 23.42 | 0.87 |

Observed proximity to roads presented in **Table 3** ranged from 0 to 0.89 km (mean = 0.20 km), and this indicates that nearly the entire study area falls within the S1 class [29]. The short average distance to roads explains the dominance of S1 in the final accessibility suitability map and indicates strong infrastructural connectivity across the landscape. In contrast, proximity to market centres ranged from 0 to 7.87 km (mean = 3.77 km), suggesting that much of the area falls within the moderately suitable and marginally suitable conditions. This spatial variability explains why, despite excellent road access, some portions were downgraded to S2 and S3 in the composite accessibility classification.

Overall, accessibility conditions in the study area are highly favourable for tea cultivation, particularly due to close road proximity. The minor proportion of marginally suitable and

non-suitable areas reflects increasing distance from central markets rather than infrastructural isolation. These findings suggest that the study area possesses strong logistical advantages for tea production, reducing transportation constraints and enhancing the economic feasibility of plantation expansion.

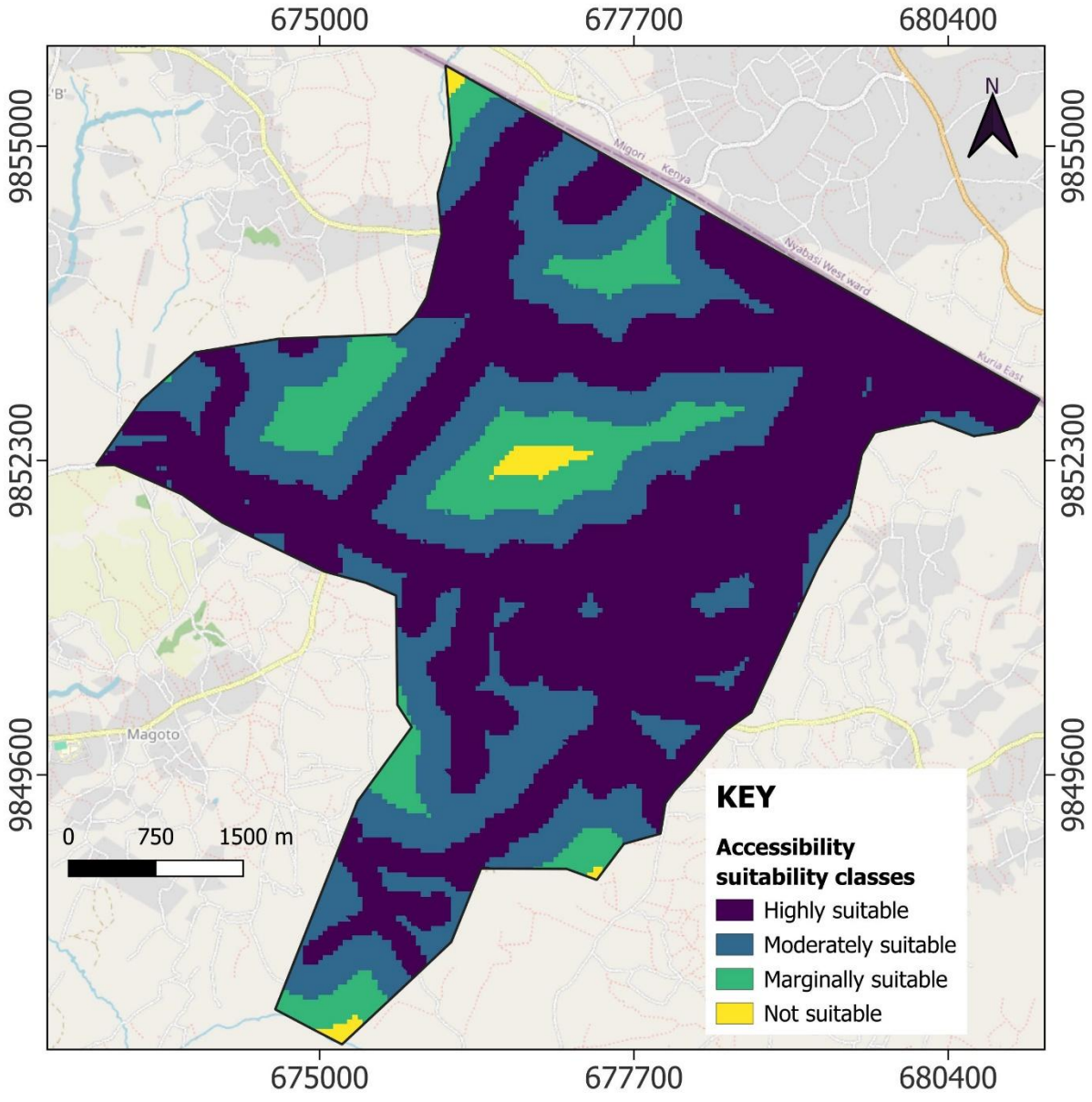



Fig. 8 Tea cultivation suitability map based on accessibility

*3.9 Overall suitability for tea cultivation*

The composite land suitability map (**Fig. 9**), generated through weighted overlay of climate, soil (chemical and physical properties), topography, land cover characteristics, and accessibility factors, reveals a predominantly favourable environment for tea cultivation. The results in **Table 16** indicate that 4.99% (133.59 ha) of the area is highly suitable (S1), 63.16% (1691.06 ha) is moderately suitable (S2), 31.80% (851.40 ha) is marginally suitable (S3), and only 0.06% (1.55 ha) is not suitable (N).

Table 13. Percentage of areas suitable for tea cultivation.

| Class | Class value | Class label | Area (ha) | Percent (%) |
|---|---|---|---|---|
| Highly suitable | 4 | S1 | 133.59 | 4.99 |
| Moderately suitable | 3 | S2 | 1691.06 | 63.16 |
| Marginally suitable | 2 | S3 | 851.40 | 31.80 |
| Not suitable | 1 | N | 1.55 | 0.06 |

The dominance of the moderately suitable (S2) class reflects the cumulative influence of factors that are generally favourable but fall slightly below optimal thresholds. Climatic conditions were largely optimal in terms of temperature [68], though rainfall levels remained within the moderately suitable range, limiting the expansion of S1 areas. Soil chemical properties showed strong suitability in terms of pH [1, 29, 68, 34, 36], and low salinity, yet moderate SOC and phosphorus levels reduced overall classification in several locations. Similarly, soil physical constraints particularly suboptimal silt proportions and variable texture contributed to marginal classifications in parts of the landscape.

Accessibility factors significantly enhanced suitability, as the majority of the area lies within 1 km of roads, ensuring efficient transport of green leaf. Land cover analysis also indicated generally favourable vegetative conditions, with high NDVI values indicating high suitability areas. However, the presence of cropland and shrubland areas reduced some zones to moderate or marginal suitability due to required land-use conversion and management adjustments.

The very small proportion of non-suitable land (0.06%) demonstrates that severe limitations are minimal within the study area. Overall, the results suggest that tea cultivation is highly feasible across most of the landscape in the study area, with productivity improvements primarily dependent on targeted soil fertility management (particularly SOC and P enhancement), structural soil improvement, and optimized water management. The predominance of S2 indicates strong potential for upgrading substantial areas to highly suitable status through appropriate agronomic and conservation interventions.

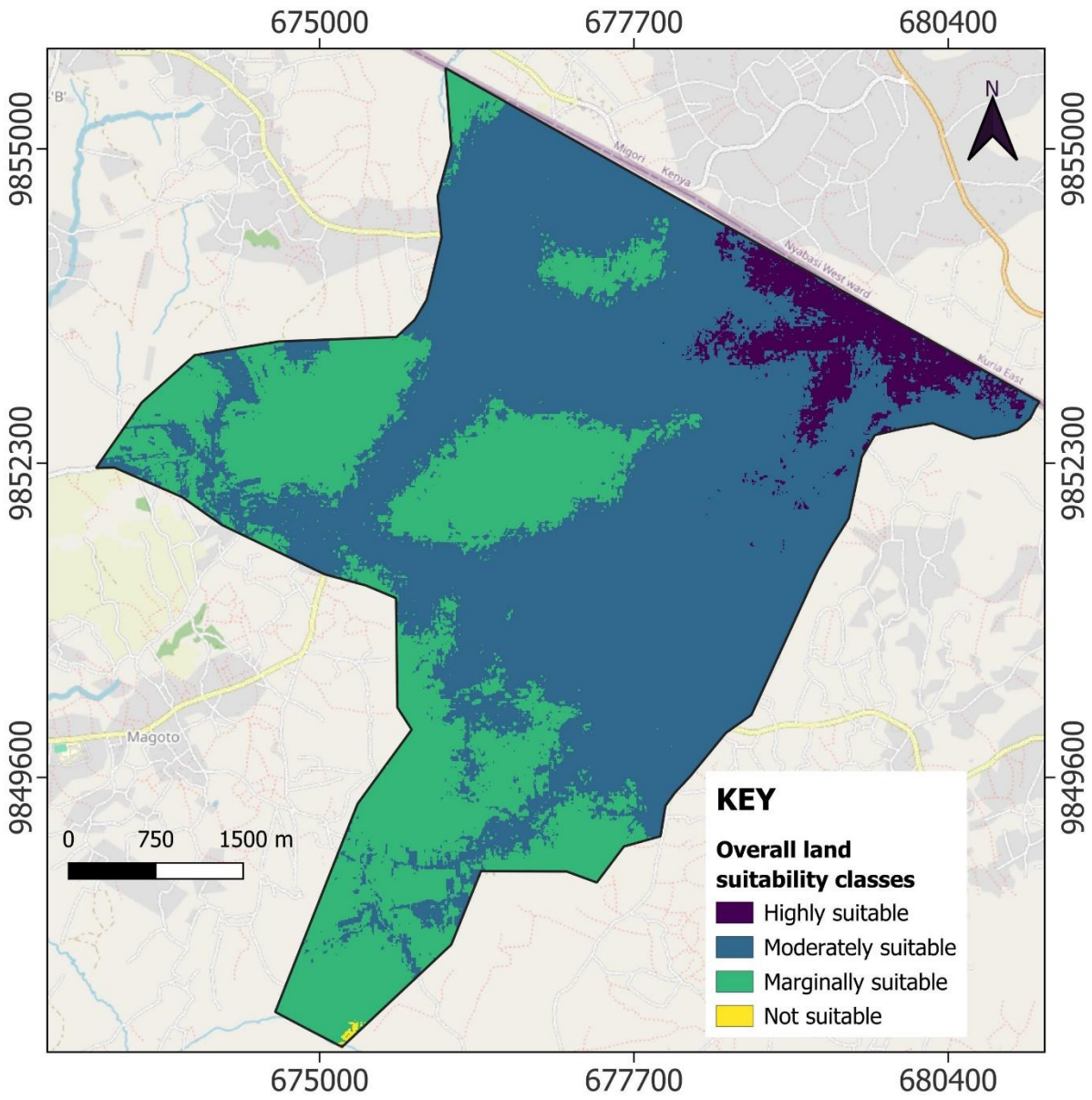



Fig. 9 Overall tea cultivation suitability map for the study area

**4 Conclusion**

This study integrated the AHP and RF modelling within a GIS-based framework to evaluate land suitability for tea cultivation in Ganyange Ward, Tarime District, Tanzania. The RF model demonstrated moderate predictive capability in mapping key soil properties relevant to tea production, with coefficient of determination ($R^2$) values for results which demonstrated positive predictive power ranging from 0.36 to 0.66. The model exhibited the strongest predictive performance for soil properties such as silt

content, electrical conductivity, and soil pH, indicating that the selected environmental covariates effectively captured spatial variability in soil conditions relevant to tea cultivation.

Through the AHP weighting process, climate emerged as the most influential factor (PW = 0.37) governing tea suitability, followed by soil chemical properties (PW = 0.25), soil physical properties (PW = 0.18), and topography (PW = 0.12), while land cover characteristics (PW = 0.05) and accessibility (PW = 0.03) played relatively smaller roles in determining overall suitability. Within these factors, rainfall, soil pH, silt content, and elevation were identified as the most influential criteria controlling tea suitability decisions.

The composite suitability analysis revealed that 4.99% of the study area is highly suitable (S1) for tea cultivation, 63.16% is moderately suitable (S2), 31.80% is marginally suitable (S3), and only 0.06% is not suitable (N). The dominance of moderately suitable land indicates that the study area generally possesses favourable conditions for tea production, although certain limitations related to soil fertility, soil texture variability, and terrain steepness constrain optimal suitability in several locations.

To improve land suitability for tea cultivation, the study recommends targeted soil fertility management strategies, particularly increasing soil organic carbon and phosphorus levels, improving soil structural stability through organic amendments, and adopting soil conservation measures on sloping terrain. These interventions could upgrade large portions of moderately and marginally suitable land to higher suitability classes and enhance sustainable tea productivity in the region.

Although the present study provides a robust spatial framework for tea suitability evaluation, further research incorporating additional environmental covariates and increased soil sampling density would enhance prediction accuracy, thereby improving the reliability of the methodology for broader application in other tea-growing regions of Tanzania.

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**Author contributions statement**

**FFM** conceptualized the study, curated the data, conducted the formal analysis and investigation, developed the methodology, acquired funding and resources, performed the software-based analysis and validation, prepared the visualizations, and wrote the original manuscript draft. **BHJM** and **HGS** contributed to the study conceptualization, data curation, formal analysis, investigation, methodology, supervision, and validation. **BEM** and **EF** contributed to the conceptualization, data curation, investigation, methodology, and validation. All authors reviewed and edited the manuscript and approved the final version.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Ethics, Consent to Participate, and Consent to Publish

Not applicable.

## Data availability

The data used in this study is published in the Mendeley Data repository at https://doi.org/10.17632/WM25P4C7NF

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