

Land Suitability Assessment for Coffee Cultivation in Nyamagabe District, Rwanda, Using GIS-Based Modelling



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Bachelor thesis, 15 credits, in Physical Geography and Ecosystem Analysis

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Abstract

Land suitability assessments for coffee cultivation can support agroecological planning and contribute to food security and economic stability in many African regions. The study identifies land suitability for coffee cultivation in Nyamagabe, Rwanda, highlighting the significant influence of air temperature, rainfall, and elevation on coffee plantations. By comparing two spatial analysis results, the current suitable areas and projected suitability, the impact of climate change is evaluated. The suitability model incorporates climatic, edaphic, topographic, and socioeconomic variables, including annual mean temperature, annual rainfall, maximum temperature of warmest month, minimum temperature of coldest month, soil texture, pH, Cation Exchange Capacity (CEC), Soil Organic Matter (SOM), elevation, slope, aspect, distance to road, and to river. Data were standardized and weighted using the criteria for coffee cultivation. Geographic Information Systems (GIS), Analytic Hierarchy Process (AHP), and Remote Sensing (RS) were integrated into the study. Future climate projection (2041-2060) under CMIP6 scenarios (SSP3-7.0) were applied for suitability analysis. The findings suggested that in the future, climate change may reduce the suitability of some current coffee-growing areas, while optimal climatic conditions are projected to shift upslope within Nyamagabe District. In the region, the current potential suitable, sub-suitable, and unsuitable areas account for 35.8%, 35.3%, and 8.1%, respectively, while Nyungwe National Park accounts for 19.3% of the total area. Under the SSP3-7.0 scenario for the 2041-2060 period, suitable and sub-suitable zones are projected to increase by 2.7% and 5.7% respectively, when unsuitable areas are projected to decrease by 7.5 percentage points compared to current levels.

KEYWORDS:

GIS-based suitability modelling, Arabica coffee plantation, Nyamagabe, AHP

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1 Introduction

1.1 General introduction

Climate change and climate variability pose significant threats to food production systems, worsening food and nutrition insecurity across Africa. The East African region is particularly vulnerable, as it is already experiencing intensified climate-related impacts, including extreme weather events, recurrent droughts, floods, landslides, and rising sea levels. These hazards undermine food security and hinder efforts to reduce poverty (Gasheja & Gatemberezi, 2017). Because agriculture in the region is predominantly rainfed, the sector remains highly sensitive to climatic fluctuations. It results in persistent food and nutrition insecurity, reducing yields, and making local food supplies unreliable (Gasheja & Gatemberezi, 2017; Ntawuruhunga et al., 2023). Trade facilitates food security in a changing climate environment by allowing countries to compensate for climate-related declines in domestic production through imports from less affected regions. As climate change increases the frequency of extreme events, trade becomes an important mechanism for climate change adaptation and mitigation, stabilizing food availability, reducing price volatility, and ensuring that households maintain access to sufficient and nutritious food (Gasheja & Gatemberezi, 2017).

The importance of Sustainable Land Management (SLM) has been emphasized by the United Nations Convention to Combat Desertification (UNCCD, 2026). Land-use productivity and sustainability depend on the interplay among natural resources, climate, and human activities. In the face of climate variability, it is critical to match land uses with specific biophysical and socio-economic conditions. Implementing SLM is essential for mitigating degradation, restoring damaged ecosystems, and safeguarding vital resources such as soil, water, and biodiversity while building climate resilience. Land degradation in highland areas contributes to declining agricultural productivity, loss of agrobiodiversity, food insecurity, and increased vulnerability to climate change. A series of measures is encouraged to enhance the adoption of resilient production systems. These include increasing land area and agroecosystems under SLM and Integrated Landscape Management (ILM) best practices, setting up a monitoring and evaluation framework, and carrying out monitoring activities (FAO, 2026).

The UNCCD (2026) stresses identifying locations best suited to land-use change required to achieve key objectives of the Sustainable Land Use System (SLUS). Shifting land-use patterns have substantial implications for sustainable agriculture. This creates a need to develop the technical capacity required to model land potential and monitor spatial-temporal trends within land-use systems to facilitate targeted local interventions. This is essential for meeting regulatory requirements and ensuring more robust monitoring and oversight.

In addition to the recommendations of SLM from UNCCD (2026) and FAO (2026), the European Union (EU) has recently introduced stringent regulatory requirements regarding the sustainability of several agrifood products, including coffee. Coffee as a popular agricultural crop is one of the most highly valued plants on the market (Fekadu & Andarege, 2025). The European Union Deforestation Regulation (EUDR) requires that commodities placed on the EU market must not originate from land that has been subject to deforestation (FAO, 2026).

These challenges eventually highlight the need for spatially explicit methods that can identify where agricultural expansion or adaptation is most viable under current and future environmental conditions. In this context, land suitability assessment offers an important decision-support tool for aligning crop production with local biophysical and socioeconomic constraints, and international regulatory requirements.

1.2 Decision Support with GIS and RS

Remote sensing (RS) and Geographical Information System (GIS) applications can provide analytical capabilities that transform spatial data to derive new insights for effective decision-making (Burrough, 1986). GIS and RS are essential tools for monitoring land use change. By providing precise spatial and temporal data, these technologies allow researchers to track agricultural conversion, identify degradation trends, and design land management strategies. Furthermore, RS provides satellite imagery and aerial photography containing monitored environmental data, while GIS serves as a spatial analysis tool that integrates diverse geographic datasets. The combination of these tools can analyze and detect large-scale changes over extended periods using historical satellite images, supporting evidence-based policy decisions, particularly regarding their impacts on agricultural productivity (Kumar et al., 2026). These insights enable policymakers to develop targeted frameworks that promote a sustainable future and mitigate environmental degradation.

Integrating GIS and Multicriteria Decision Analysis (MCDA) to bridge the concepts and methods of these two distinct fields, offering new ways to address complex decision problems (Malczewski & Rinner, 2015). Suitability analysis as a decision-support process is a widely used GIS-based method (Burrough, 1986; Kumar et al., 2026). It is commonly applied to identify the most appropriate locations for specific land-use objectives. In spatial decision-making, suitability and hazard maps are examples of results derived from suitability analysis; they display the spatial distribution of the determined values in a graphical form. This process is achieved through an intersection of social, ecological, economic, physical, or other criteria. Consequently, the combination of decision-support techniques with GIS offers a wide range of robust approaches.

Within this GIS-MCDA framework, the Analytical Hierarchy Process (AHP) introduced by Saaty (Saaty, 2005) serves as a fundamental multicriteria methodology and is a cornerstone of many coffee suitability models. Identifying suitable locations for coffee cultivation is a complex challenge in land science that requires the integration of diverse environmental variables (Fekadu & Andarege, 2025). This analysis typically employs GIS-based weighted overlay techniques and AHP to synthesize climatic data (temperature, precipitation), topographic factors (elevation, slope, and aspect data), and edaphic properties (soil texture, pH, CEC), while incorporating Land Use Land Cover (LULC) data to account for landscape constraints (Birhanu et al., 2024; Nigussie et al., 2024; Rono & Mundia, 2016).

1.3 The Role of Coffee in Rwanda

In Rwanda, about 90% of the population depends on subsistence farming, agriculture is a foundational economic pillar of Rwanda and shaped by a highly diversified agroecological landscape. These agroecological differences provide an important basis for agricultural planning, including the identification of crop potential, production risks, and appropriate land management strategies (Gasheja & Gatemberezi, 2017). High dependence on agriculture, coupled with low productivity, remains a significant challenge for Rwanda. The sector is constrained by land fragmentation (Nzeyimana et al., 2013), limited mechanization, post-harvest losses, and climate change. Despite these challenges, the World Bank (2025) emphasized that the agricultural sector in this country still holds significant growth potential, creating quality jobs and boosting forex earnings. In addition, a comparison between Rwanda and countries that transitioned from low- to upper-middle income status suggests that Rwanda should identify and focus on its competitive advantages and prioritize them (Uwizeyimana, 2024).

Although coffee is the leading agricultural export of Rwanda (FAO, 2026), many coffee farmers in the land are smallholders operating on a scale too small to secure sustainable

livelihoods. Coffee net income, in general, constitutes 43.4% of the total household income. It is estimated that farmers need a minimum of 800 to 1,000 coffee trees to sustain coffee farming activities and generate sufficient income to improve their livelihoods (ICO, 2024; World Bank, 2025). In addition to improving productivity and lowering production costs through agronomic resource management, including targeted agricultural practices such as fertilization, mulching, and pruning as well as growing more productive coffee trees, it is also essential to consider farm size. As a predominantly agricultural country, Rwanda should also consider farm size and the sustainable use of natural resources when defining its competitive advantages and development priorities (ICO, 2024).

The coffee sector in Rwanda has faced systematic stagnation for more than two decades, primarily because farmers were not included as full partners in the country's specialty coffee transformation, particularly as production incentives (such as farm-gate prices) have been too low (Clay et al., 2018). These governance and incentive failures have discouraged farmers from investing in their coffee plots, resulting in low productivity, aging trees, poor farm management, and stagnant national production. Recent policy shifts suggest some of these problems are being addressed and significantly mitigated, leading the coffee industry into a recovery phase. In 2025, coffee farmers received an average of 900 RWF/kg for cherry coffee, well above the 600 RWF/kg benchmark set by the National Agricultural Export Development Board (NAEB).

A major reform in 2023 changed the landscape through liberalization. The government abolished the mandatory zoning policy within the coffee sector (ICO, 2024). According to the previous policy (2016-2023), under the old zoning rules, farmers were legally required to sell their coffee cherries only to a designated Coffee Washing Station (CWS) within their specific geographic zone. After the 2023 reform, farmers are now free to sell their cherries to any buyer nationwide, which has triggered intense competition and significantly increased cherry prices.

To counter the trend of farmers abandoning coffee for other crops due to low profitability, the government has launched aggressive interventions. For example, replacing coffee trees that are more than 30 years old to increase production. The most benefited regions include Western Province, Nyamagabe, Huye, and Southern Province; rehabilitation programs will be conducted for coffee trees over 7 years old. Furthermore, it is expected to create more jobs and thereby drive the entire industry (NAEB, 2026).

Beyond its role as a vital cash crop that enhances net income, coffee systems that integrate a diversified income portfolio promote the overall sustainability and socio-economic advancement of farming communities (ICO, 2024). This refers to value addition in coffee production through vertical integration, efficiency improvements, and income distribution of the value chain. Farmers who join cooperatives that also process, dry-mill, and export coffee can triple their incomes. This is because they capture value beyond the farm gate, not just selling cherries, but participating in milling, quality control, and export margins. Agritourism is another way to increase income, using the farm for tours or workshops to attract visitors (Nyamagabe District, 2024).

In Rwanda, coffee plantation sites are primarily determined by smallholder farmers, but their decisions are heavily influenced and structured by government bodies (e.g., NAEB), cooperatives, and coffee washing stations (CWSs). Smallholders typically own and cultivate highly fragmented land parcels, with individual plots averaging less than a quarter hectare per household. The decision to plant coffee is a part of a broadly coordinated national strategy to ensure high-quality, fully washed *Coffea arabica* (ICO, 2024; Hakorimana et al., 2019). The CWSs employ mainly women for drying operations during the harvesting season, and men oversee land clearing, planting seedlings, stumping and pruning coffee trees, as well as technical practice (AgriLogic, 2018). Coffee provides a critical livelihood for more than 350 000 farmers, 40% of whom are women", according to FAO (2026).

1.4 Ecosystem Services of Coffee-based Agroforestry

Alongside the economic and social benefits that the coffee industry can provide, a coffee-based agroforestry system can substantially increase carbon storage in that land. Every 100 tons of carbon stored in a conventional sun-grown coffee plantation, a shaded agroforestry system of the same size would store roughly 177 tons (SEI, 2024). This additional carbon is stored in two main ways: above-ground biomass, including the trunks, branches, and leaves of the shade trees; and below-ground biomass, comprising deeper root systems and increased organic matter in the soil. A 77% increase suggests that coffee agroforestry is a potentially effective agricultural strategy for climate change mitigation. It allows farmers to produce a cash crop while simultaneously functioning like a mini forest. Therefore, these systems contribute to the recovery of degraded land and build ecosystem resilience against climate shocks.

Moreover, the litter layer in a mulched coffee plantation provides natural protection that mitigates soil erosion, particularly when runoff rates are within the moderate range of 10 to 30% (Roose & Ndayizigiye, 1997). Through the integration of the agroforestry systems with coffee production, it can provide the biomass needed for mulch; the primary challenge is the ability to produce sufficient organic matter to effectively cover the entire soil surface. It is noted that adopting agroforestry coffee farming systems can enhance Soil Organic Matter (SOM), improve soil structure, and increase coffee productivity by using nitrogen-fixing trees such as *Leucaena*, *Calliandra*, and *Tephrosia*, while protecting soils from erosion. Coffee, as a perennial crop, is better than annual crops at avoiding soil disturbance (Nzeyimana et al., 2013).

Most agricultural land in Rwanda is located on steep hillsides, which are also used for coffee cultivation. Soil erosion on these slopes highlights a significant challenge to standard farming practices. Intercropping coffee with food crops increases competition for essential resources and contributes to a decline in coffee production (Nzeyimana et al., 2013). However, the researchers also state that because intercropping prevents the soil surface from being left bare, it can help limit soil erosion, particularly in marginal environments such as steep upper hillside slopes (Roose & Ndayizigiye, 1997). This integrated system may offer a significant benefit by reducing dependence on eucalyptus trees, a dominant forest type in Rwanda that can contribute to soil degradation, by providing alternative resources for fuel and timber (Figure 1). Eucalyptus trees create a “biological desert” via allelopathic suppression of the understory (Clay, 2026) and have an inverse effect on the habitats of birds and other wildlife (Wintgens, 2004).



Figure 1. Eucalyptus monoculture plantations cause soil erosion and landslides in Nyamagabe District. Photo source: Nyamagabe District (2024).

1.5 Importance of *Coffea arabica*

Arabica is a small coffee tree species, originally from the Abyssinian plateau of Ethiopia (Birhanu et al., 2024). In Africa, it is grown primarily in high-altitude regions, yielding high-quality coffee (FAO, 1977). The major production zones for Arabica cultivation besides the Kivu region include Central America, Colombia, the Mexican highlands, and the Andean zone. In Africa, key regions include the Ethiopian plateau, Mount Elgon in Uganda, and the East African highlands; other notable areas include the Brazilian highlands, the mountains of India, Central Java in Indonesia, and the Cameroon highlands (Wintgens, 2004).

Approximately 99% of the total coffee output from Rwanda is *C. arabica*, consisting mainly of the Bourbon and Typica varieties (ICO, 2024). This coffee is primarily grown at high altitudes (()) on steep slopes with low-fertility soils, while subsistence crops are generally reserved for more fertile areas (Nzeyimana et al., 2014).



Figure 2. Coffee plantation in Nyamagabe District.

Photo source: Liping Lu

According to Nzeyimana et al. (2014), Rwanda is divided into 10 agroecological zones: Imbo, Impara, Birunga, the Lake Kivu shores, the Congo-Nile Watershed Divide, the Buberuka Highlands, the Central Plateau, Mayaga-Bugesera, the Eastern Plateau, and the Eastern Savanna (Figure 3). Much of the land suitable for *Coffea arabica* is located along the shores of Lake Kivu; these high-altitude sites are prioritized for *C. arabica* production due to their particularly moderate and exceptionally stable climate year-round.

1.6 Hypothesis and Objectives

Previous studies have demonstrated the usefulness of GIS-based multi-criteria analysis for coffee suitability assessment in countries such as Ethiopia, Kenya, and Rwanda. However, these studies have either focused on other regions, emphasized current suitability only, or have not examined district-level future suitability shifts in Nyamagabe. This study aims to combine biophysical and socioeconomic criteria in a GIS-AHP framework to assess both current and projected coffee suitability in Nyamagabe District. In particular, the study contributes a spatially explicit analysis of how climate change may alter the geography of coffee production within this district. The future analysis is based on the SSP3-7.0 scenario for the 2041-2060 period. This scenario represents a relatively high-emissions pathway and is useful for assessing potential climate risks under stronger warming conditions. Including this scenario makes it possible to evaluate whether currently suitable coffee-growing areas remain viable and whether suitability is likely to shift toward higher elevations, which is highly relevant for long-term agricultural planning and climate adaptation.

In this study, a spatial multi-criteria suitability model will be developed to identify suitable areas for coffee agroforestry in Nyamagabe District, Rwanda, using GIS, remote sensing, and ecological constraints. Additionally, the study seeks to assess the spatial impact of climate change on coffee production. The study hypothesizes that the climate suitability for coffee in Nyamagabe District will undergo a spatial shift, with optimal growing conditions migrating toward higher elevations under the SSP3-7.0 climate scenario for the 2041 – 2060 period.

Objectives:

1. Develop a multi-criteria land suitability model for Nyamagabe District.
2. Generate current and future suitability maps for coffee cultivation.
3. Evaluate the model by comparing the suitability results with the locations of existing coffee sites.

2 Study Area

Nyamagabe District serves as a microcosm of Rwanda, characterized by limited land resources and a growing population (Ntawurunga et al., 2023). The Nyamagabe District Land Use Plan (NDLUP) outlined several strategies to drive economic value in the district. For example, value-enhancing strategies include expanding high-value crops, such as tea, coffee, wheat, Irish potatoes, implementing land consolidation to increase productivity, and utilizing improved agricultural practices. Forestry and wood processing are also included in a value-adding chain. Tourism opportunities and ecotourism projects are framed as a value-creating economic sector (Nyamagabe District, 2024).

This study focuses on Nyamagabe District, located in the southwest part of Rwanda, with a total area of 1090 km² (Figure 3). Topographically, the district extends across the Congo-Nile watershed divide agroecological zone and transitions into the western fringes of the Central Plateau (Nzeyimana et al., 2014). The administrative boundaries of the district are roughly defined by the UTM coordinates 751,896 to 796,546 m E and 9,756,621 to 9,712,311 m S (zone 35S). The regional elevation ranges from 1514 to 2924 m, shaping a highly rugged, mountainous landscape. The climate of Nyamagabe District is characterized as temperate tropical highland, with a temperature consistently ranging between 15 °C and 25 °C throughout the year. It exhibits a bimodal rainfall pattern, with an average annual precipitation of 1200 to 1600 mm which is distributed across four distinct seasons: two relatively dry intervals (January to February and July to mid-September), and two pronounced rainy seasons (March to June and mid-September to December). Additionally, localized climates differ markedly across the landscape, dictated by complex topography, with hillslope aspect and elevation gradients drive significant microclimatic heterogeneity (Avelino et al., 2005; Ochoa et al., 2017).

Similar to the other regions where Arabica coffee thrives, the environmental conditions of Nyamagabe District are well suited to its physiological requirements. However, due to the smallholder systems of Rwanda, low planting densities in this region limit the canopy's protective effect, leaving large portions of the soil surface exposed and vulnerable to erosion (Nzeyimana et al., 2013). Consequently, Nyamagabe was selected because of the interplay between its favorable agroecological conditions and its constraints which is a critical factor for regional coffee suitability planning. Furthermore, agricultural expansion must be carefully balanced with the conservation of biodiversity in Nyungwe National Park, as mandated by NDLUP (Nyamagabe District, 2024).

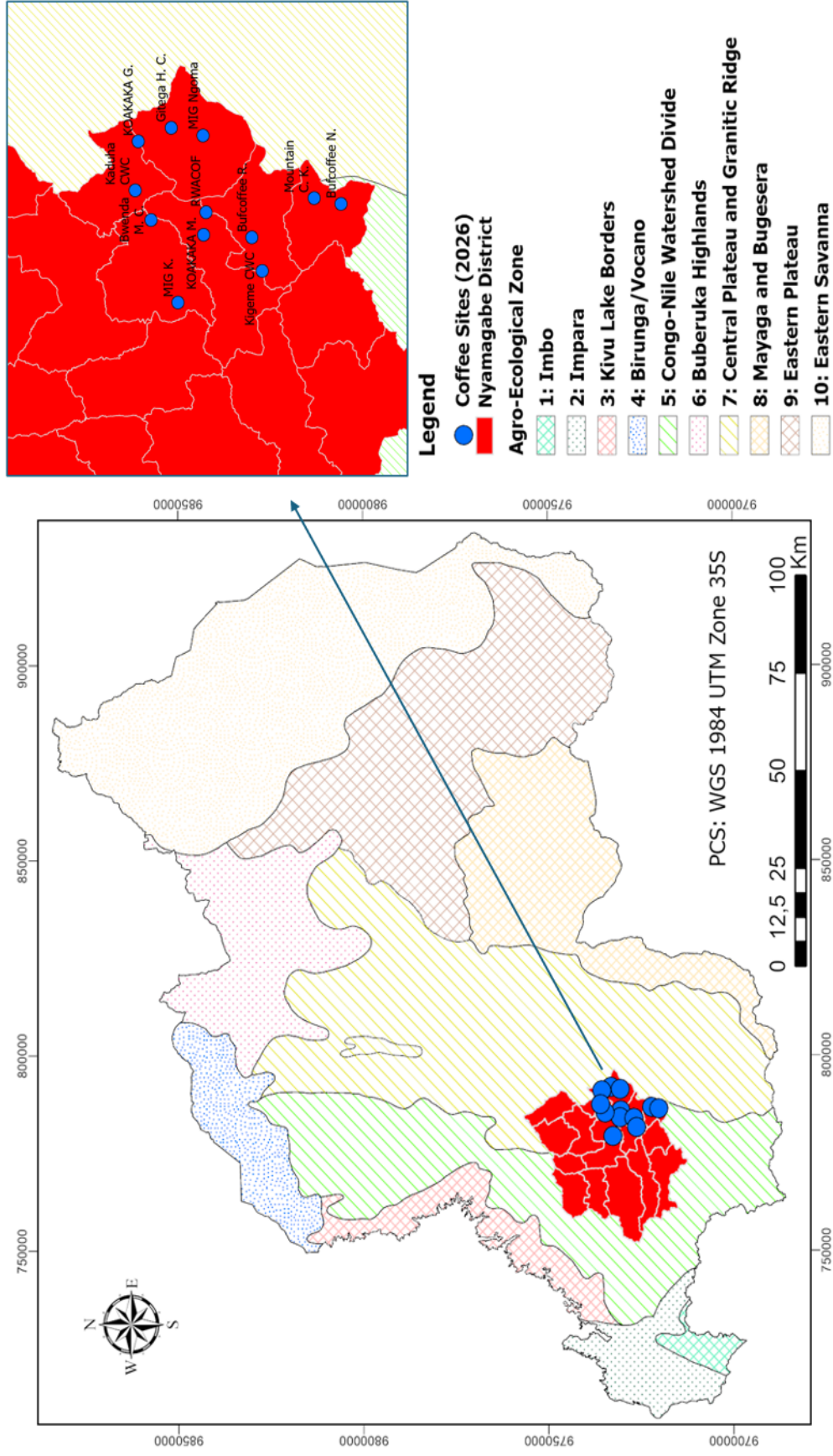


Figure 3. The location of the study area shows Nyamagabe District a) spans two distinct agroecological zones: the Congo-Nile watershed divide, and the central plateau and granitic ridge; b) a total of 12 existing coffee sites.

3 Materials and Methods

3.1 Data and Preprocessing

All data sets (Table 1) used for suitability analysis are referenced in a projected coordinate system. They were processed and imported into the ArcGIS Pro geodatabase as feature classes and raster layers. The World Geodetic System 84 (WGS 84) was used as the geographic coordinate system, and WGS 1984 UTM zone 35S was selected as the projection. This centralized geodatabase environment ensured that the various criteria could be standardized into a common measurement framework for subsequent analysis.

The previous research by Nigussie et al. (2024) mapped the LULC classification using a combination of Sentinel-1 data and field data in Ethiopia. However, in the absence of a comprehensive, field-derived land cover reference dataset for Nyamagabe District, this study applied a pre-processed product to map existing LULC patterns and estimate current spatial coffee coverage. This provides the foundation for identifying and prioritizing suitable land for coffee cultivation in Nyamagabe using a GIS-AHP framework. The selected dataset is the Sentinel-2 10m land use/land cover time series of the world (the year 2025), derived from European Space Agency (ESA) Sentinel-2 L2A imagery. This product was collaboratively developed by Esri and Impact Observatory and was obtained via direct cloud access within the ArcGIS Pro (v3.4) environment. This dataset leverages deep learning AI classification models trained on billions of human-labeled pixels to automatically distinguish nine globally standardized vegetation and structural types, including water, flooded vegetation, cropland, trees, rangeland, bare ground, built area, snow/ice, and clouds. This approach leverages a widely accepted, pre-classified spatial dataset to extract existing land cover patterns and establish the current coffee distribution baseline for the study area, ensuring that the foundational layers of the multi-criteria model rely on highly accurate, standardized datasets.

WorldClim bioclimate data were used to model the climatic thematic layer. The historical bioclimate variables (1970-2000) were utilized as a baseline, including annual mean temperature, annual precipitation, and temperature extremes. For the comparative analysis, the MPI-ESM1-2-HR general circulation model was used to extract the projected future bioclimatic variables. These variables were derived from the CMIP6-based SSP3-7.0 scenario for the 2041–2060 period at a spatial resolution of 30 arc-seconds. As a primary dataset for the IPCC Sixth Assessment Report (AR6), CMIP6 ensures that this assessment of climate change impacts on coffee suitability is grounded on the most current and authoritative global climate science. The SSP3-7.0 pathway was included as a high emissions scenario to assess potential worst-case impacts on temperature stress, precipitation variability, and coffee suitability. This future dataset facilitates a robust valuation of potential environmental shifts.

Soil properties, including soil texture, pH, SOM, and CEC, were obtained from the open-access SoilGrids datasets. These variables represent key edaphic factors that influence coffee growth and were integrated as sub-criteria in the suitability model. Soil texture was determined using clay, silt, and sand content data. Data from SoilGrids were initially provided in decigrams per kilogram (dg/kg). These were converted to percentages through a depth-weighted average calculation (Eq.1) for the 0-30 cm profile to align with agronomic standards for coffee cultivation (Hengl & et al., 2017). This same standardization process was applied to pH, CEC, and SOM.

$$\frac{1}{b-a} \int_a^b f(x) dx \approx \frac{1}{(b-a)} \frac{1}{2} \sum_{k=1}^N (x_{k+1} - x_k) (f(x_k) + f(x_{k+1})) \quad \text{Eq. 1.}$$

Where N is the number of depths, x_k is the k -th depth, and $f(x_k)$ is the value of the target variable at depth x_k .

The soil texture map was generated (Appendix II, Figure A3a) using USDA soil texture classification standards (FAO, 1985),.

Physiographic factors are critical for assessing erosion risk, solar exposure, and microclimatic conditions relevant to coffee cultivation. Therefore, the topographic layers, i.e., slope, aspect, elevation, were derived from a 10-meter Digital Elevation Model (DEM). This high-resolution dataset was released as open data by the National Land Authority (NLA) of Rwanda and accessed via the United Nations Development Programme (UNDP) GeoHub. Utilizing this terrain data to ensure accurate topographical analysis of the study area.

In addition to LULC, the socioeconomic data were incorporated, specifically road networks and DEM-generated river networks, following FAO (2007) guidelines. Euclidean distances to roads and rivers were computed based on these data.

To ensure mathematical compatibility during the multi-criteria overlay process, the datasets were resampled to a unified 10-meter cell size using the 10-meter DEM. Specifically, the climate layers (temperature, rainfall) and edaphic properties (soil texture, pH, CEC, and SOM) were standardized using Bilinear Interpolation. The discrete Land Use/Land Cover (LULC) grid was resampled using the Nearest Neighbor method.

Table 1: Datasets used in the project.

Datasets	Description
Province Boundary	Vector data: used to extract the study area boundaries. Source: Land soil crop information hubs https://rwanda.lsc-hubs.org/
2025 Sentinel-2 10m Land Use/Land Cover Time Series	Raster data: used as a constraint mask and to identify the LULC classification. Source: Esri and Impact Observatory
Digital Elevation Model (DEM), Rwanda	Raster data: 10 m resolution, used to extract altitude, aspect, slope, and stream. Source: National Land Authority and United Nations Development Programme, date year 2024. https://geohub.data.undp.org/api/datasets/00d5add9be37e465398b081683c3ec03
Bioclimate: historical and future climate scenario SSP3-7.0, period 2041- 2060	Raster data, a spatial resolution of 30 arc-seconds, including annual mean temperature, annual precipitation, max temperature of the warmest month, and min temperature of the coldest month. Source: WorldClim
Soil texture, organic matter, cation exchange capacity, and pH	Tiff format with a resolution of 250m, 0 – 30 cm layer, provided by Africa Soil Information Services, https://soilgrids.org
Existing coffee sites	Coffee sites, resource from the National Agricultural Export Development Board (NAEB), Rwanda
Rwanda roads	Shapefile, used for extracting the distance to the road network; downloaded from Humanitarian Data Exchange.
Protected areas in Rwanda	Shapefile, used for excluding the Nyungwe National Park from the calculation of suitability analysis; the data is available at www.protectedplanet.net

3.2 Methodology for Suitability Assessment

In accordance with the land evaluation framework (FAO, 2007), the variables required for the suitability analysis were extracted from multiple datasets. These variables were subsequently reclassified and ranked in a GIS environment to generate suitability scores for each thematic layer. Finally, the weighted overlay tool was used to integrate all layers, producing the final suitability maps. The complete methodology workflow is illustrated in Figure 4.

The Agro-Ecological zoning (AEZ) model, integrated with socioeconomic factors, was used to map suitable areas for coffee cultivation in the study area. The modeling process began with an analysis of climate, geomorphology, and soil conditions to determine the biophysical suitability based on Arabica coffee's specific requirements.

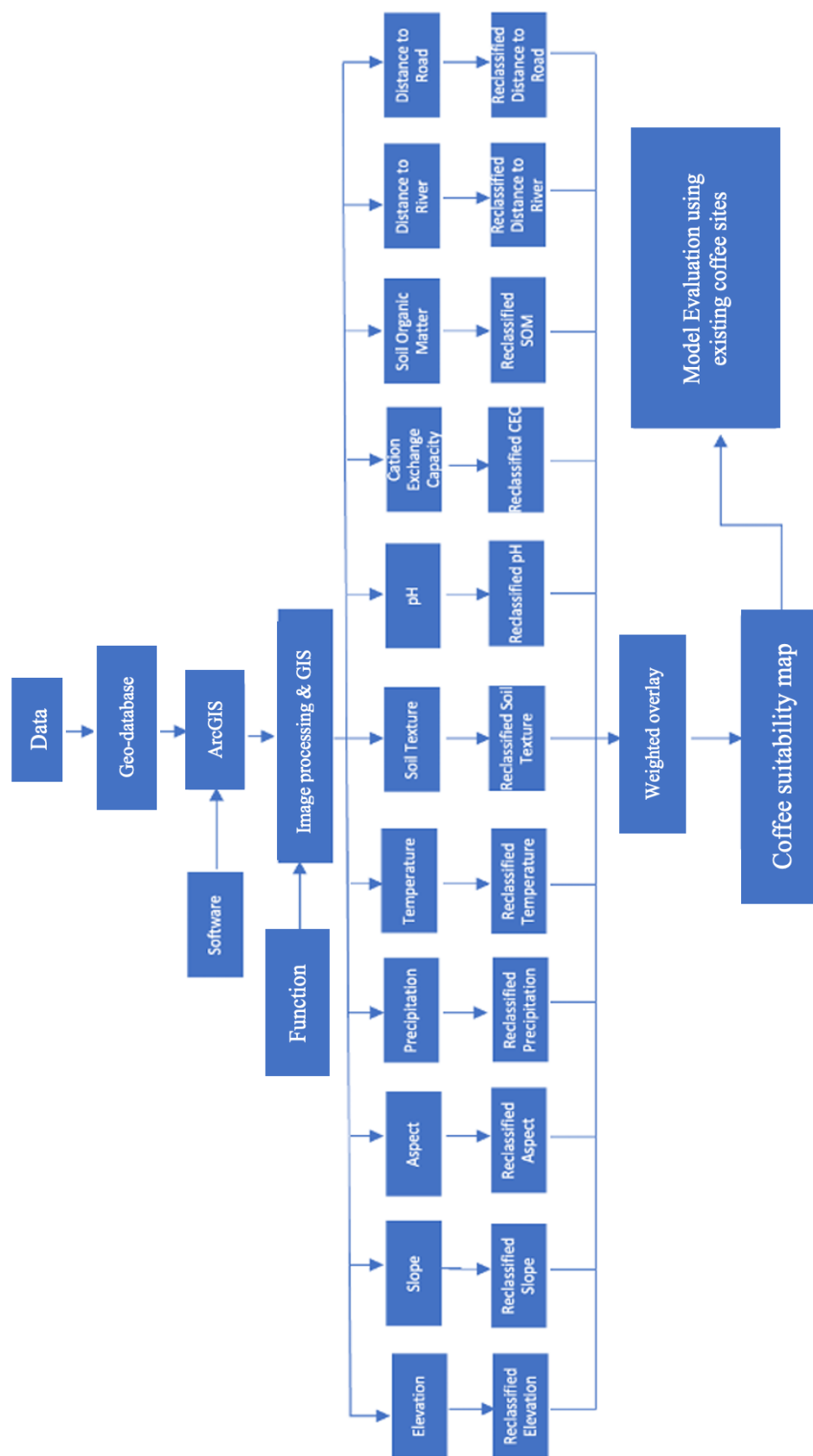


Figure 4. Methodological flowchart of the research.

3.3 Criteria Determination for Arabica

Factors considered in evaluating land suitability for Arabica coffee production included soil qualities (fertility, chemical, and physical), topographic factors (slope, elevation, and aspect), Land Use and Land Cover (LULC), and climatic variables. Many researchers have studied suitability modeling for Arabica cultivation (Birhanu et al., 2024; Cunha et al., 2023; Fekadu & Andarege, 2025; Nigussie et al., 2024; Nzeyimana et al., 2014; Ochoa et al., 2017; Rono & Mundia, 2016). They use three main factors to determine coffee production: environmental conditions (e.g., topography, soil type, climate, and elevation), agricultural land management practices, and genetic resources (i.e., coffee varieties). Wintgens (2004) proposed that appropriate sites for coffee cultivation should be selected with respect to six basic environmental factors, i.e., temperature, water availability, sunshine intensity, wind, soil types, and topography.

Cultivation of high-quality *Coffea arabica* in Rwanda relies on precise environmental parameters. Structurally, the crop requires an altitudinal range of 1,400–1,900 meters above sea level, matched with an annual rainfall of 1500–1600 mm, a temperate thermal profile of 18–22°C, and 2200–2400 annual solar hours. Edaphically, successful growth demands a minimum soil depth of 1 meter coupled with a fine texture, a total porosity of 50–60%, an acidic pH threshold between 4.5 and 6.0, and an organic matter content of 2–5%. Researchers used soil orders (USDA taxonomy), including Andisols, Alfisols, Inceptisols, Ultisols, Oisols, Entisols, Histosols, and Mollisols, as indicators for physical properties and texture, rather than specific textural classes, e.g., clayey, loamy sandy (Nzeyimana et al., 2014).

Accordingly, the criteria used in this study were established through a literature review and informed by expert knowledge from coffee agronomy. The selected factors encompass from four domains: meteorology, topography, edaphic properties (comprising physical and chemical soil characteristics), which are biophysical determinants for coffee growth; and socioeconomic conditions (LULC, distance to road and river), which directly influence the economic viability for coffee production. Summarized biophysical and socioeconomic requirements for Arabica coffee were gathered from the various literature (Table 2). These variables would be tested and then used to establish the specific criteria for the study area, providing the foundation for reclassifying each thematic layer into suitability classes.

Table 2. The synthesized parameters used to determine coffee cultivation suitability.

Variables	Criterion	Reference
Temperature (°C)	15-26	Nzeyimana et al. (2014); Nigussie et al. (2024); Wintgens (2004); Ochoa et al. (2017)
Precipitation	1000-2000.	Nzeyimana et al. (2014); Nigussie et al. (2024)
Elevation (m a.s.l)	1000-2500	Nzeyimana et al. (2014); Nigussie et al. (2024); Birhanu et al. (2024)
Slope (%)	0-25	Nzeyimana et al. (2014); Nigussie et al. (2024)
Aspect	north (N), northeast (NE) northwest (NW) east (E), west (W)	Nigussie et al. (2024)
Soil texture	clay, clayey-silty silty-clayey, loam silty-clayey-sandy silty-sandy, sandy-silty	Wintgens (2004); Nigussie et al. (2024); Birhanu. et al. (2024)
pH	4.5-6.0	Nzeyimana et al. (2014); Wintgens (2004)
CEC (mol c/kg)	>15	Nigussie et al. (2024); Wintgens (2004)
SOM (%)	> 2	Nigussie et al. (2024); Ochoa et al. (2017)
Distance to River (km)	< 5	Nigussie et al. (2024)
Distance to Road (km)	< 5	Nigussie et al. (2024)

CEC = cation exchange capacity SOM = soil organic matter

3.4 Data Classification

Suitable land for coffee cultivation was identified using the land suitability evaluation guidelines outlined by (FAO, 2007). This revision promotes the use of MCDM and automated tools like GIS and RS to handle these more complex, overlapping criteria. Hence, in this study, many criteria and sub-criteria were used to rank the alternatives of a decision. It referenced the suitability models that were developed in the previous research carried out in the neighboring countries of Rwanda, such as Ethiopia, Kenya, and ensured geographical relevance in variable selection (Birhanu et al., 2024; Nigussie et al., 2024; Nzeyimana et al., 2014; Ochoa et al., 2017; Rono & Mundia, 2016).

The raster data was prepared through categorization, standardization, and reclassification. After being split into four individual thematic layers (Appendix II, Figures A1-A5), the geographical data were reclassified and redisplayed to match the new data structure (Figures 10-14). The reclassification of all variables used a three-level scale: Suitable (3 scores / Class S1), Sub-suitable (2 scores / Classes S2/S3), and Unsuitable (1 score / Class N), according to the FAO (2007) scoring system.

Additionally, for the LULC layer of the model by Nigussie et al. (2024), active farmland and grassland were restricted to a sub-suitable ranking, while existing agroforestry zones were treated as optimal. In contrast, this study designed existing croplands as suitable to delineate core agricultural zones positioned for strategic Climate-Smart Agriculture (CSA) interventions. Concurrently, tree cover and rangelands were reclassified as Sub-Suitable, designating them as transitional vegetative buffers. In alignment with both frameworks, residential areas were strictly excluded as Unsuitable, ensuring an absolute zoning constraint.

The thoughts about reclassifying tree covers and rangelands as sub-suitable and designating them as transitional vegetative buffers imply that while these open spaces are not currently cultivated, they represent ideal geographic baselines for conversion into structured coffee agroforestry systems. Introducing managed coffee farming into these existing rangeland areas allows smallholders to use semi-natural vegetation as a foundation to shield vulnerable soils from erosion while scaling sustainable production.

Table 3 is thus based on the previous studies of Arabica coffee (Table 2), especially the two work by Nigussie et al. (2024), whose study area shares similar biophysical conditions with Nyamagabe, and Nzeyimana et al. (2014), who conducted nationwide coffee research in Rwanda. The primary criteria and sub-criteria were selected for each thematic layer, derived from biological thresholds of Arabica and relevant socioeconomic factors required for the land suitability analysis of the study area. A standardized ordinal rating scale from 1 to 3 was applied to the attribute values in ArcGIS Pro, where a score of 3 denotes suitable areas for ideal criteria for Arabica coffee; a score of 2 is sub-suitable areas that needs some land management (e.g., terrace, fertilizing) to help coffee growing; a score of 1 represents unsuitable areas, where coffee cannot survive.

Table 3. The classification of criteria and sub-criteria.

Sub-Criteria/Criteria	Suitable (3)	Sub-suitable (2)	Unsuitable (1)
Climatic thematic layers			
Annual rainfall (mm)	1200-1800	1000-1200, 1800-2000	> 2000, <1000
Annual mean temperature (°C)	16-22	15-16, 22-26	<15, > 26
Max Temperature of Warmest Month	< 25	25 -30	> 30
Min Temperature of Coldest Month	> 18	10 - 18	< 10
SSP3-7.0 for period 2041 - 2060			
Annual rainfall (mm)	1200-1800	1000-1200, 1800-2000	> 2000, <1000
Annual mean temperature (°C)	16-22	15-16, 22-26	<15, > 26
Max Temperature of Warmest Month	< 25	25 -30	> 30
Min Temperature of Coldest Month	> 18	10 - 18	< 10
Edaphic thematic layers			
Texture (texture class)	Sandy clay loam	Sandy clay, clay loam	Clay
pH	5-6	4.5-5.0	< 4.5
SOM	>3	2 - 3	< 2
CEC (cmol + /kg)	>25	15-25	< 15
Physiographic thematic layers			
Elevation (m above sea level)	1400 -1800	1000-1400; 1800-2500	<1000; > 2500
Slope (%)	0-12	12 - 25	> 25
Aspect	N, NE, NW	E, W	S, SW, SE
Socioeconomic thematic layers			
LULC	Cropland	Trees/rangeland	Water/flooded vegetation/built area/ bare ground
Distance to river network (km)	0-1	1-5	>5
Distance to road network (km)	0-2	2-5	>5

3.5 AHP-Based Derived Weights for Coffee Suitability

A GIS-based multi-criteria evaluation approach integrated with Analytic Hierarchy Process (AHP) was employed to assess the spatial suitability of coffee cultivation under current and future climate scenarios (Nigussie et al., 2024; Nzeyimana et al., 2014; Saaty, 2005)

In general, the AHP was applied to assign weights to the evaluation criteria, following the framework established by Saaty (2005). In the ideal AHP model, a fundamental prerequisite is that the criteria remain entirely independent from the decision alternatives (Saaty, 2005). Through this process, the relative priorities of the biophysical, land-use, and accessibility criteria are calculated, which can directly drive the generation of the final relative weights. The Pairwise Comparison Matrix (PCM) is a key component of the AHP process, providing a mathematically structured way to quantify expert judgment and translate qualitative importance into consistent numerical scales.

CR is a diagnostic measure used in AHP to check whether the pairwise comparisons are logically consistent. A CR value ≤ 0.1 indicates acceptable consistency, whereas values above this threshold require revision of the comparison matrix (Nigussie et al., 2024; Rono & Mundia, 2016; Saaty, 2005).

In many decision-making problems, like coffee suitability models, there is no objective formula that determines how important one factor is when compared to another; expert judgment is needed. Through the PC matrix, experts compare two criteria at a time, and these comparisons are transformed into numerical weights. As a prevalent method, AHP assigns weights by capturing the opinion of experts in the multiple criteria decision making, to improve the quality of decision-making (Kuo & Chen, 2023). This approach improves transparency, reduces ambiguity, and allows the logical consistency of expert judgments to be evaluated through the Consistency Ratio (CR) (Saaty, 2005).

According to the ArcGIS Pro documentation (Esri, 2026b), the CR is computed using the formula below:

The Consistency Index (CI)

$$CI = \frac{\lambda - n}{n - 1} \quad \text{Eq. 2}$$

Where:

- λ : the primary eigenvalue presents the average of the λ_i for each variable.
- n : the number of input variables.

$$\lambda_i = \frac{SW_i}{w_i} \quad \text{Eq. 3}$$

Where:

- w_i is the derived weights for each input variable.
- SW_i reflects the weighted sum for each variable i .

$$SW_i = \sum_{j=1}^j a_{ij} \cdot w_j \quad \text{Eq. 4}$$

Where:

- a_{ij} is the value from the original pairwise comparison matrix, where i and j represent the row and column, respectively.
- w_j donates as the derived weights of the corresponding variables.

The Random Index (RI) is a predefined statistical constant determined strictly by the order (size) of the pairwise comparison matrix.

Matrix size	2	3	4	5	6	7	8	9
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Finally, CR is calculated using the ratio of consistency index (CI) and random consistency index (RI):

$$CR = CI / RI \quad \text{Eq. 5}$$

The researchers (Fekadu & Andarege, 2025; Nigussie et al., 2024; Ochoa et al., 2017) suggested the usefulness of AHP when combined with GIS, and this method is essential for identifying the suitability of a location for coffee planting. Inconsistent judgements can distort the derived weights and compromise the reliability of the suitability model, so that a low CR value is needed and must be ensured.

Hence, this study adopted the weighting scheme (Table 4) from the approach by Nigussie et al. (2024), owing to its low CR value of 0.029 and the close topographic similarities between the Gedeo Zone in Ethiopia and the Nyamagabe district. The relevant pairwise comparison matrices were presented in Table A1 and A2 (Appendix I). Since the weights were from a previous study rather than derived from a new local expert elicitation process, it may introduce uncertainty into the final suitability model.

Table 4. Weights of multicriteria decision analysis, adopted from Nigussie et al. (2024).

Main Factor	Weight	CR	Factor	Weight	CR	Final Weight	%
Climate	0.6	0.029	Mean annual rainfall	0.27	0.03	0.162	16.2
			Average annual temperature	0.39	0.03	0.234	23.4
			Annual mean min temperature	0.13	0.03	0.078	7.8
			Annual mean max temperature	0.21	0.03	0.126	12.6
Edaphic	0.16	0.029	pH	0.37	0.008	0.0592	5.92
			Texture	0.28	0.008	0.0448	4.48
			CEC	0.2	0.008	0.032	3.2
			SOM	0.15	0.008	0.024	2.4
Physiographic	0.15	0.029	Elevation	0.65	0.001	0.0975	9.75
			Slope	0.21	0.001	0.0315	3.15
			Aspect	0.14	0.001	0.021	2.1
Socioeconomic	0.09	0.029	LULC	0.6	0.01	0.054	5.4
			Distance to road	0.23	0.01	0.0207	2.07
			Distance to river	0.17	0.01	0.0153	1.53
Total						1	100

The suitability index presented in Figure 10 was derived by extracting all raster pixels within each coffee site and computing a weighted average across the suitability maps. The weights from Table 4 were applied to each criterion layer, and the resulting weighted overlay produced a single composite suitability value per site.

3.6 Evaluation and Analysis

The final decision map visualizes the continuous suitability scores of the final raster derived from the GIS-AHP Weighted Linear Combination (WLC). Because the resulting index values clustered within a narrow numerical interval, the spatial variations in suitability between the baseline and future scenarios were evaluated and compared by implementing a standardized classification threshold schema. First, the baseline suitability scores were categorized using the Natural Breaks (Jenks) algorithm (Onglassynov et al., 2025), which minimizes variance within classes while maximizing variance between them (Malczewski & Rinner, 2015). Through this process, the continuous landscape spectrum of Nyamagabe District was delineated into three discrete operational suitability classes: suitable, sub-suitable, and unsuitable. The score range for the classes derived from the baseline map were subsequently applied to the future scenario map via Manual Interval classification, to ensure strict comparability. This uniform thresholding ensures that any observed geographic expansion or contraction of suitability zones reflects actual model dynamics. The comparison with existing coffee sites should be interpreted as a plausibility check rather than a full predictive validation of the model. Crucially, the presence of coffee at a given location does not necessarily indicate optimal productivity; however, it provides a valuable empirical reference for assessing whether modelled suitability is broadly consistent with observed cultivation patterns.

Subsequently, model evaluation was executed on the final classification accuracy of the generated suitability zones, a critical process commonly supported through the spatial overlay of empirical field reference points (Nigussie et al., 2024; Onglassynov et al., 2025). In this study, the evaluation was conducted utilizing independent verification site data obtained from NAEB. Twelve coffee sites in the study region, indicated by blue dots in Figure 3, were used for suitability analysis, and their exact geographic locations are detailed in Table A3 (Appendix I).

In addition, a Pearson Correlation analysis (Schober et al., 2018; Wilcox, 2003) was performed in Excel to examine the interdependencies between environmental variables. This step was used to explore relationships among environmental variables in the study area and to assess whether logic patterns were broadly consistent with the assumptions underlying the suitability model.

4 Results

4.1 Reclassified Climatological Thematic Layers

Climatological thematic layers (Figure 5) illustrate that the annual mean temperature, annual precipitation, maximum temperature of the warmest month, and minimum temperature of the coldest month, originally shown in Figure A1, were each reclassified into three rating classes. Figure 5a shows that for the annual mean temperature, more than 50% of the study area was classified as suitable (16-20 °C). Annual precipitation ranged from 1200 to 1800 mm across the study area, and the entire area was therefore classified as suitable with respect to precipitation (Figure 5b).

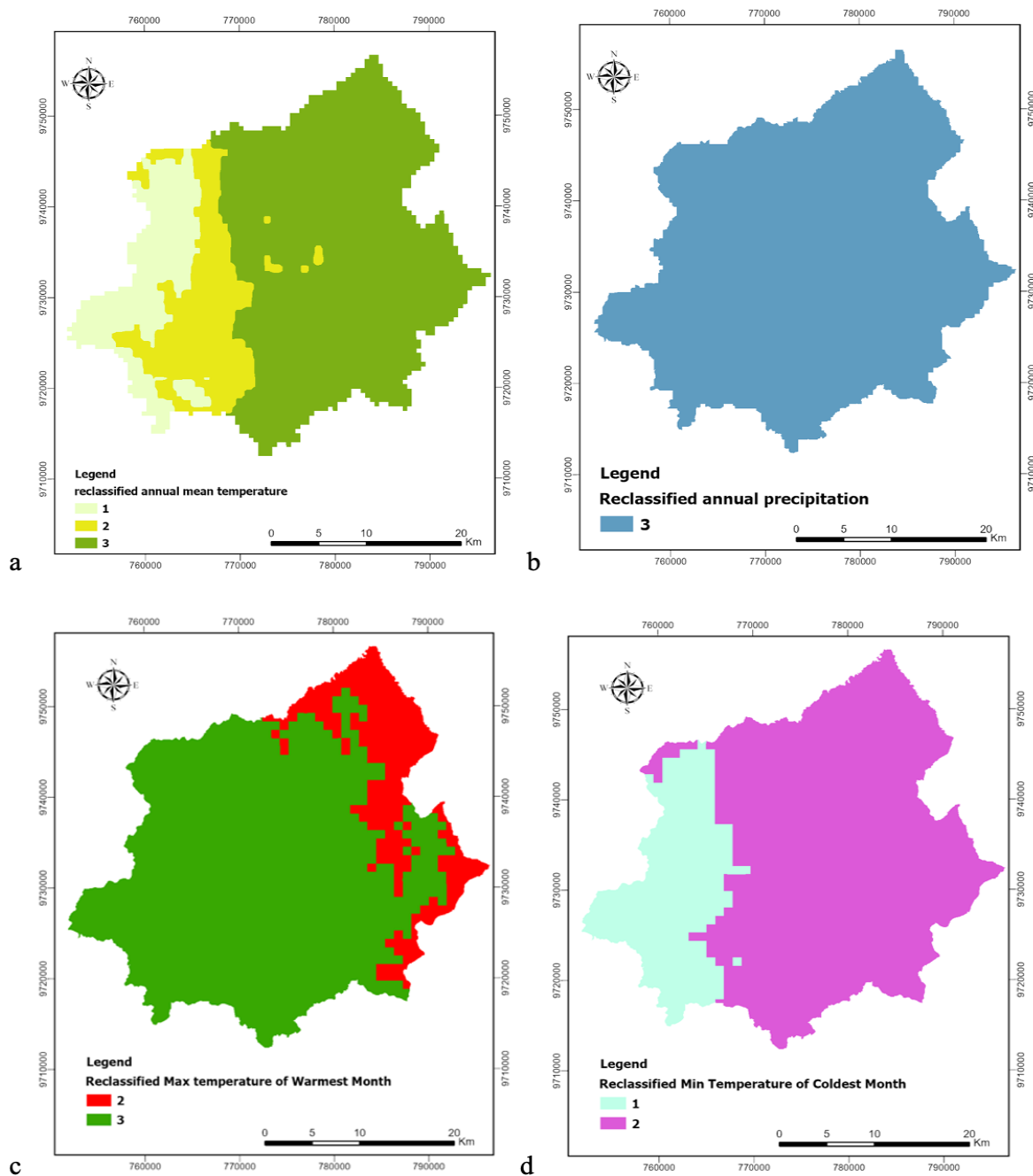


Figure 5. Maps of climatological thematic layers: a) reclassified annual mean temperature, b) reclassified annual precipitation, c) reclassified maximum temperature of warmest month, d) reclassified minimum temperature of coldest month.

Figure 6 illustrates that under the future climate scenario, with increased annual mean temperature, almost 90% of the study area is classified as suitable for coffee (Figure 6a). Conversely, suitability based on annual precipitation declines slightly under the future scenario, with a small area in the western part of the district becoming classified as sub-suitable (Figure 6b). Figure 6c shows that the areas with the maximum temperature of the warmest month are split between suitable and sub-suitable categories, as Figure 6d shows that the minimum temperature of the coldest month is predominantly classified as sub-suitable.

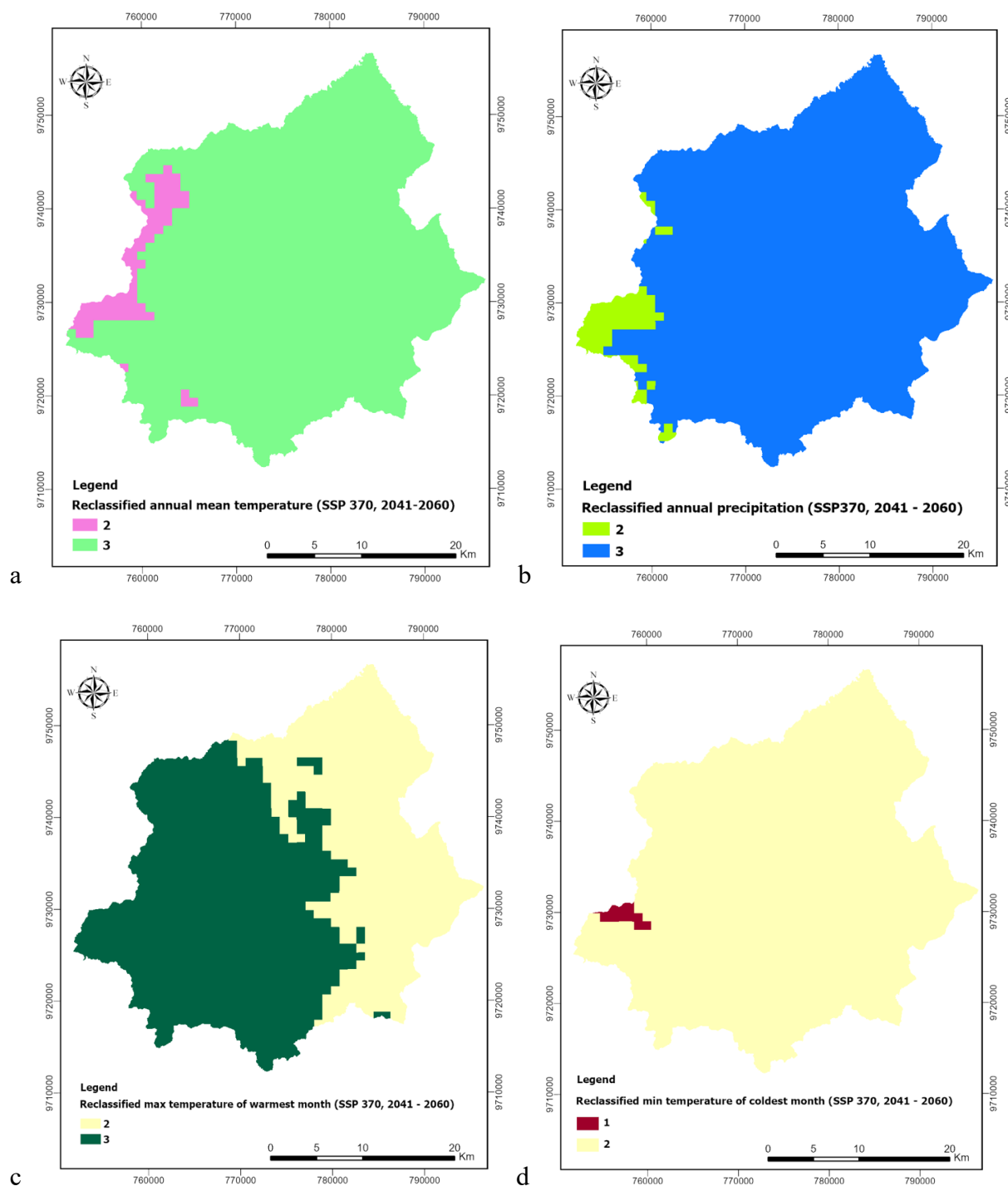


Figure 6. Maps of future climate scenarios SSP 370 for the 2041 – 2060 period: a) reclassified annual mean temperature, b) reclassified annual precipitation, c) reclassified maximum temperature of warmest month, d) reclassified minimum temperature of coldest month.

4.2 Reclassified Physiographic Thematic Layers

Physiographic thematic layers (Figure 7) illustrate that the highest elevations in western Nyamagabe are classified as unsuitable. Sub-suitable regions extend from the west to the east, accounting for the largest portion of the area. The relatively lower terrain spanning the northern to eastern parts is classified as suitable (Figure 7a). Maps 7b and 7c display the variation in suitability-based slope and aspect.

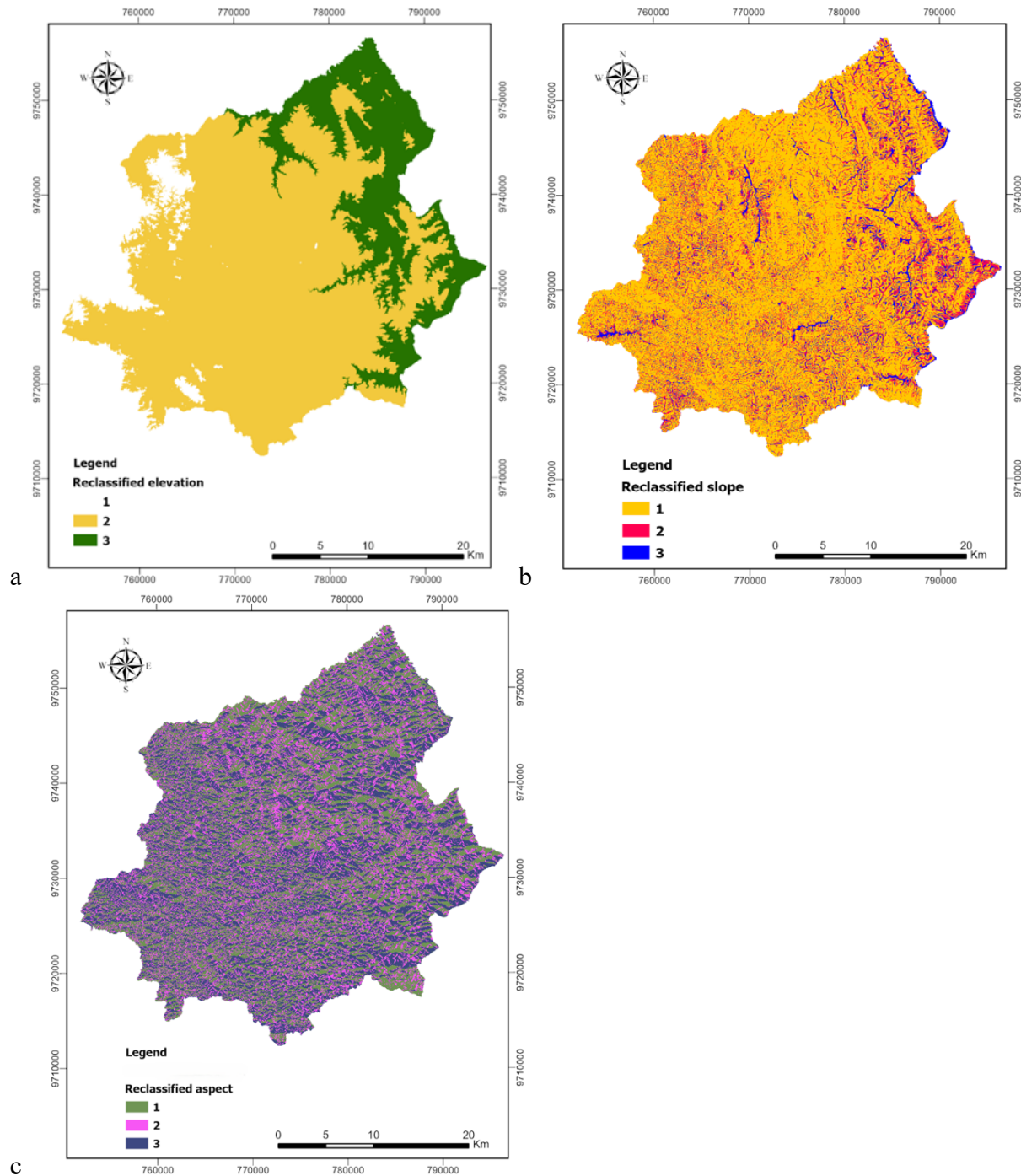


Figure 7. Maps of the physiographic thematic layers: a) reclassified elevation, b) reclassified slope, c) reclassified aspect.

4.3 Reclassified Edaphic Thematic Layers

Edaphic thematic layers (Figure 8) illustrate that the dominant soil types are clay loam and sandy clay. Areas surrounding Nyungwe National Park are the most suitable due to higher SOM and CEC, while the eastern part of the district is sub-suitable for coffee plantation. Soil pH is almost evenly distributed between suitable and sub-suitable categories.

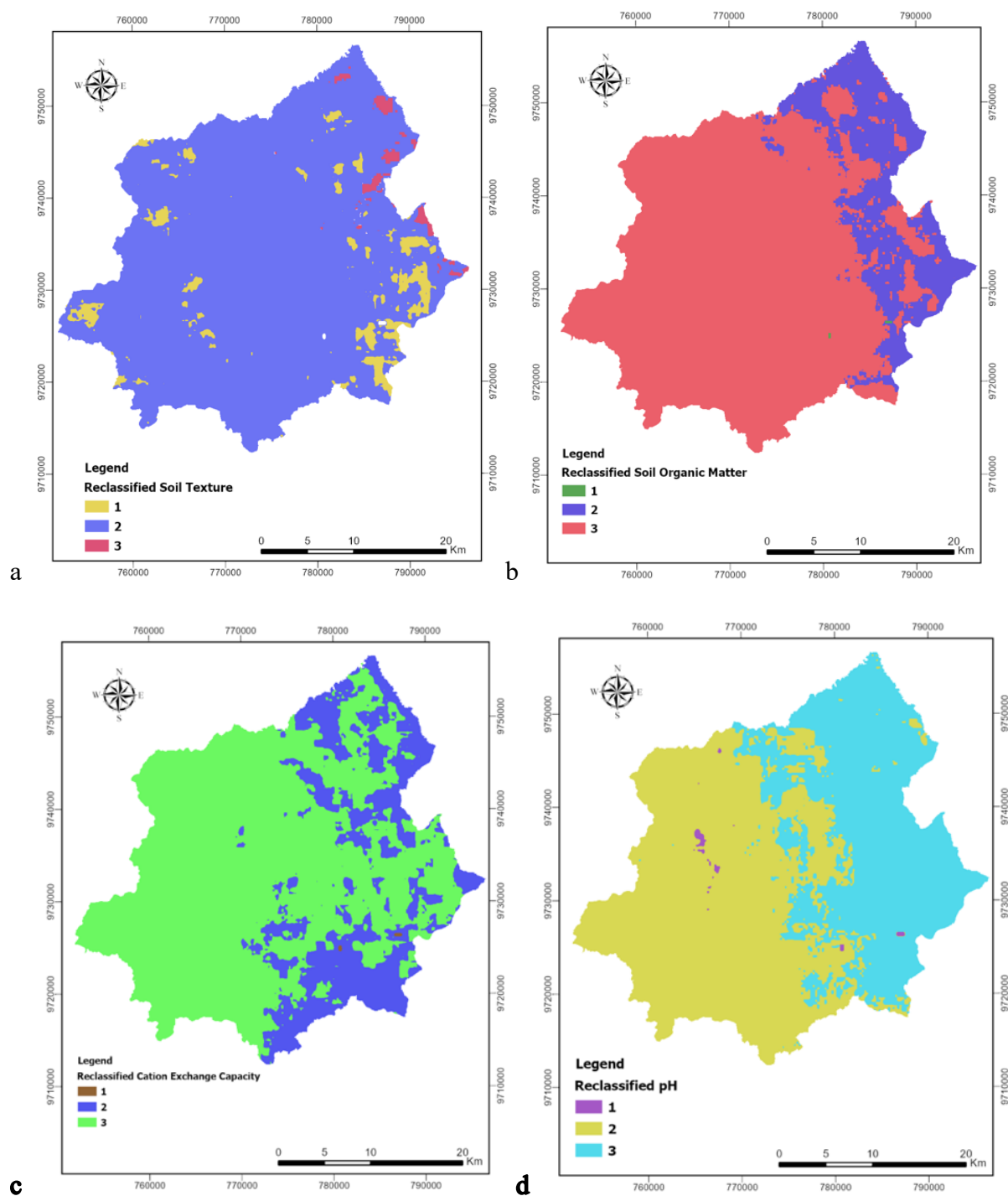


Figure 8. Maps of edaphic thematic layers: a) reclassified soil texture, b) reclassified soil organic matter, c) reclassified cation exchange capacity, d) reclassified soil pH.

4.4 Reclassified Socioeconomic Thematic Layers

Socioeconomic thematic layers (Figure 9) illustrate that the LULC layer, Euclidean distance to road, and river have been reclassified according to the criteria.

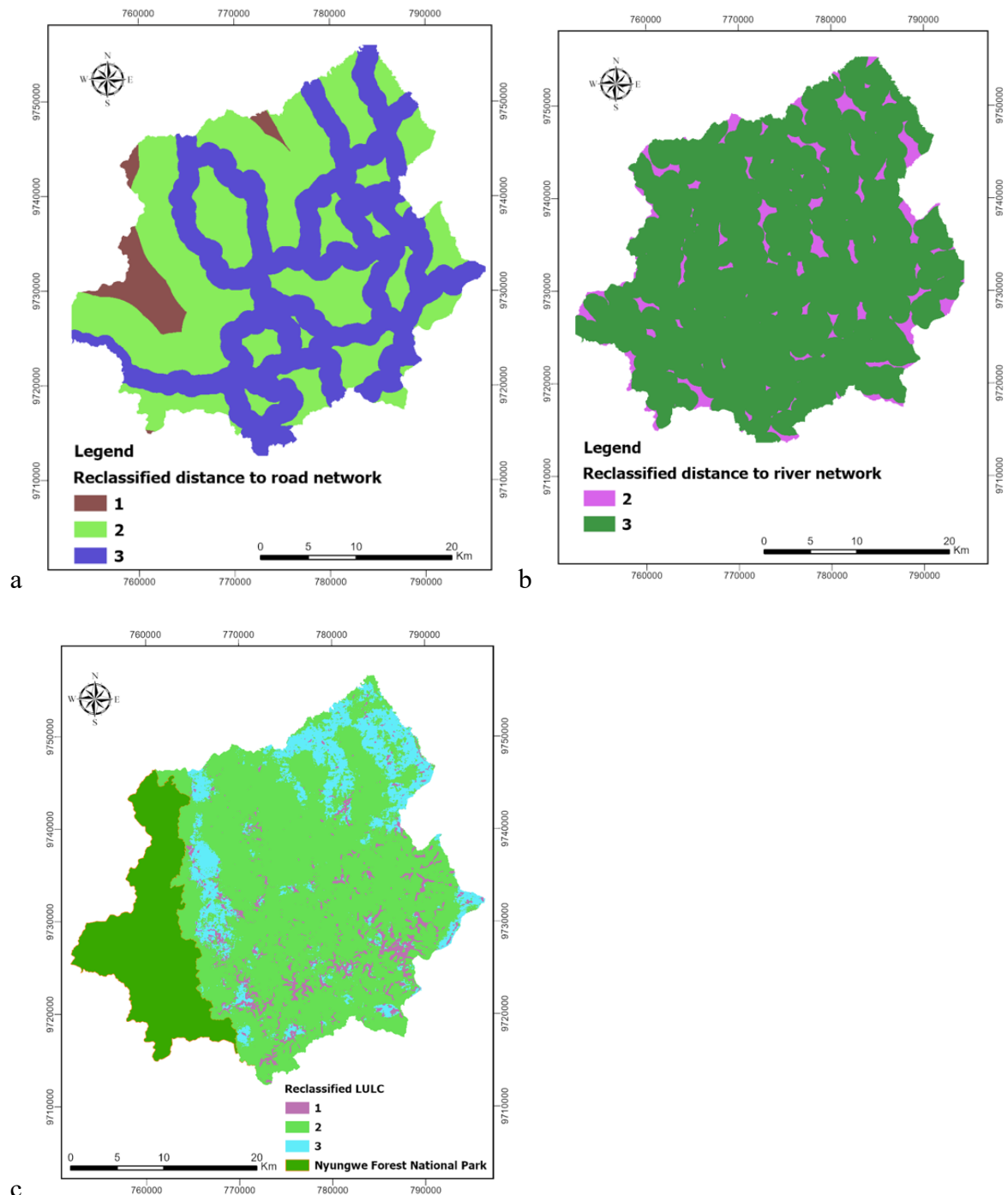


Figure 9. Maps of socioeconomic thematic layers: a) distance to road network, b) distance to river network, c) Land use and land cover classification.

4.5 Suitability Analysis

Table 6 shows a very strong negative linear correlation between elevation and temperature ($r = -0.93$), indicating that as elevation increases, temperature decreases. A strong positive correlation ($r = 0.75$) was also observed between elevation and precipitation. This indicates that higher-altitude sites in the study area receive significantly more rainfall, likely due to orographic effects, which directly influences the distribution for Arabica coffee. A strong negative correlation was found between temperature and precipitation ($r = -0.79$), indicating that warmer sites in the study area receive significantly less rainfall. Another strong positive correlation was found between elevation and SOM ($r = 0.78$).

Figure 10 illustrates the differences between the current and the projected suitability for Arabica coffee at 12 existing sites in Nyamagabe. Seven of these twelve coffee sites are projected to experience a decline in suitability under future climate scenarios, while the suitability of the remaining five sites remains unchanged.

The validation of sampling sites (Figure 11) illustrates that the existing coffee locations share highly consistent temperature and precipitation regimes. It is observed that annual precipitation, annual mean temperature, and distance to rivers at these evaluated sites fell entirely in the suitable class. In contrast, 9 sites were found to have unsuitable slopes. Regarding the maximum temperature of the warmest month and road distance, 9 sites were classified as suitable. For soil textures, 7 sites were categorized as sub-suitable and 5 as unsuitable. In terms of the hillslope aspect, 5 sites were classed as suitable, 4 sites as sub-suitable, and 3 as unsuitable. Regarding the LULC layer, six sites for sub-suitable and six as unsuitable.

The spatial distribution of current suitable areas (Figure 12 for coffee cultivation was identified using the fourteen thematic layers. The results indicate that the highly potential areas extend from the eastern to the central regions, with suitability gradually decreasing toward the unsuitable zones (denoted by orange). Most current coffee sampling sites are located within suitable areas, while a small number of sample points are positioned between the suitable and sub-suitable classes. The areas unsuitable for coffee production are mainly concentrated in the western parts of the district. The suitable and sub-suitable coffee-cultivating potentials accounted for 35.8% and 35.3% of the total study area, respectively (Figure 14a, Table 5). Unsuitable land constitutes the remaining 8.1% of the total area.

Figure 13 depicts that suitable areas for coffee cultivation are projected to migrate from the eastern regions toward the western areas near Nyungwe National Park, according to the SSP3-7.0 scenario for the 2041–2060 period. Most sub-suitable areas are found in the northern and southeastern parts of the study area. Notably, some previously unsuitable zones are projected to show an improvement in suitability, whereas existing coffee production areas are expected to experience a decline. In this projected scenario, suitable and sub-suitable areas account for 38.5% and 41.1% of the district, respectively, while unsuitable land for coffee growing decreases to just approximately 0.5% of the total area (Figure 14b, Table 5).

Table 5. Potential suitable areas for coffee production.

Classification	Current Area (Km ²)	Projected Area (Km ²)	Current Coverage (%)	Projected Coverage (%)
Suitable	390	420	35.8	38.5
Sub-suitable	385	448	35.3	41.1
Unsuitable	88	5	8.1	0.5
Nyungwe National Park	210	210	19.3	19.3

Table 6. Pairwise Pearson Correlation matrix of the variables.

R	Elevation	Slope	Aspect	Temperature	Precipitation	pH	CEC	SOM	Distance to Road	Distance to River
Elevation	1.00	0.59	-0.31	-0.93	0.75	-0.63	-0.12	0.78	-0.12	0.04
Slope	0.59	1.00	-0.15	-0.52	0.47	-0.36	-0.28	0.27	-0.34	0.24
Aspect	-0.31	-0.15	1.00	0.26	-0.11	0.23	-0.65	0.06	0.01	0.47
Temperature	-0.93	-0.52	0.26	1.00	-0.79	0.58	0.07	-0.88	-0.02	0.06
Precipitation	0.75	0.47	-0.11	-0.79	1.00	-0.87	-0.36	0.76	-0.26	-0.16
pH	-0.63	-0.36	0.23	0.58	-0.87	1.00	0.27	-0.56	0.29	0.36
CEC	-0.12	-0.28	-0.65	0.07	-0.36	0.27	1.00	-0.21	0.17	-0.38
SOM	0.78	0.27	0.06	-0.88	0.76	-0.56	-0.21	1.00	0.11	0.05
Distance to Road	-0.12	-0.34	0.01	-0.02	-0.26	0.29	0.17	0.11	1.00	-0.10
Distance to River	0.04	0.24	0.47	0.06	-0.16	0.36	-0.38	0.05	-0.10	1.00

R values:

0.90 to 1.00: Very strong correlation;

0.70 to 0.89: Strong correlation;

0.40 to 0.69: Moderate correlation.

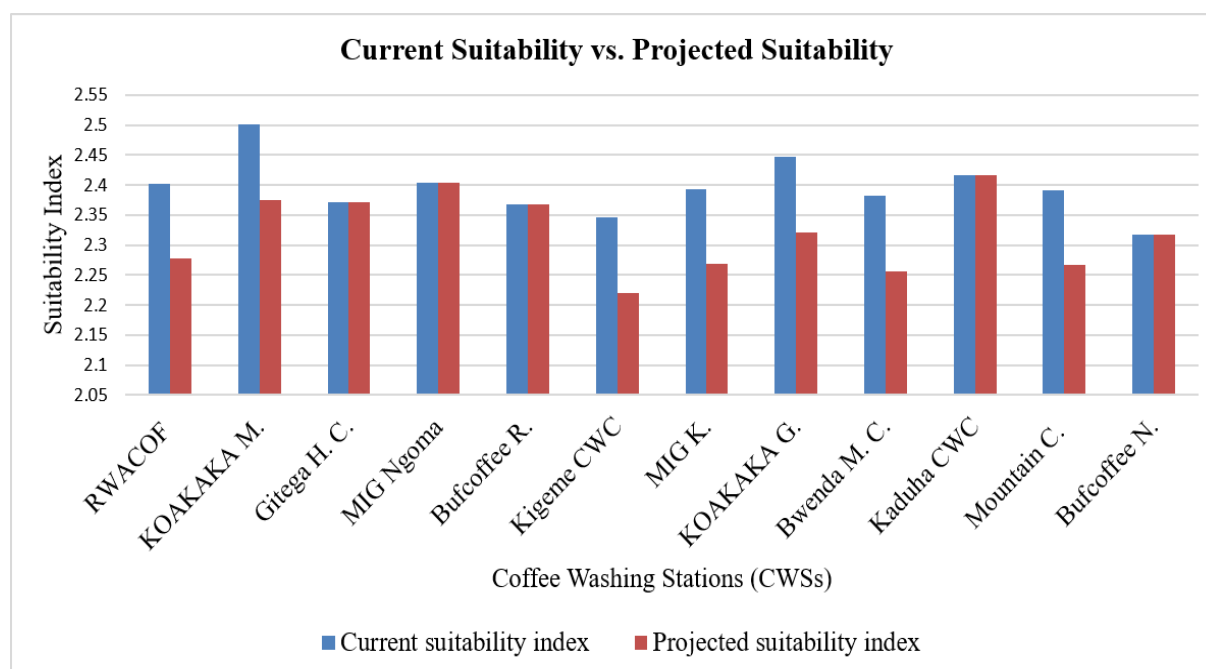


Figure 10. Comparison of current suitability and projected suitability indices for 12 sampling points, which derived from the final suitability maps. The projected suitability index represents the modelled suitability score at each existing coffee sites under the SSP3-7.0 future climate scenario for 2041-2060, while the current suitability index represents the score under baseline climate conditions. Higher index values indicate relatively better overall suitability for coffee cultivation.

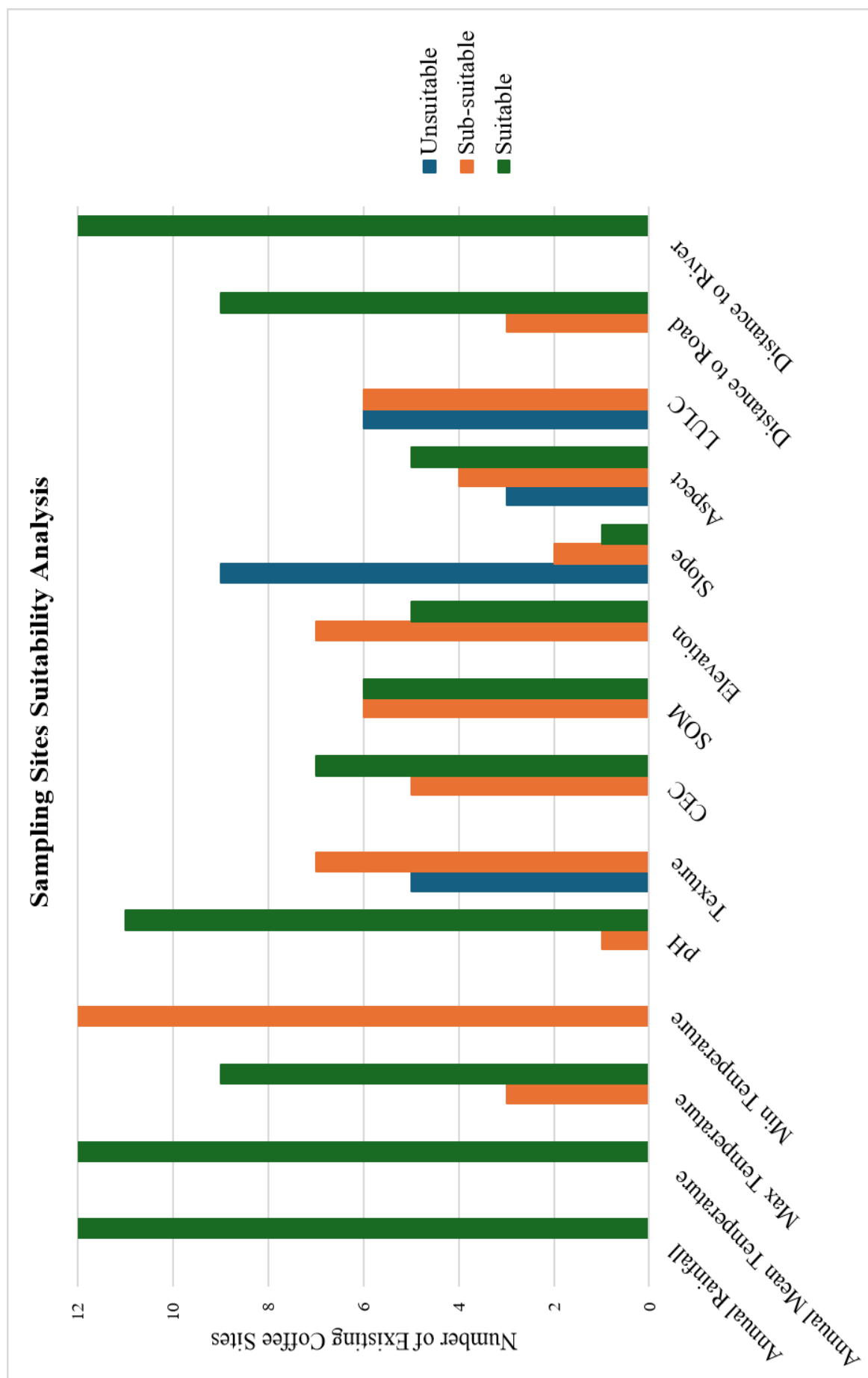


Figure 11. Suitability analysis of the environmental factors at 12 sampling sites.

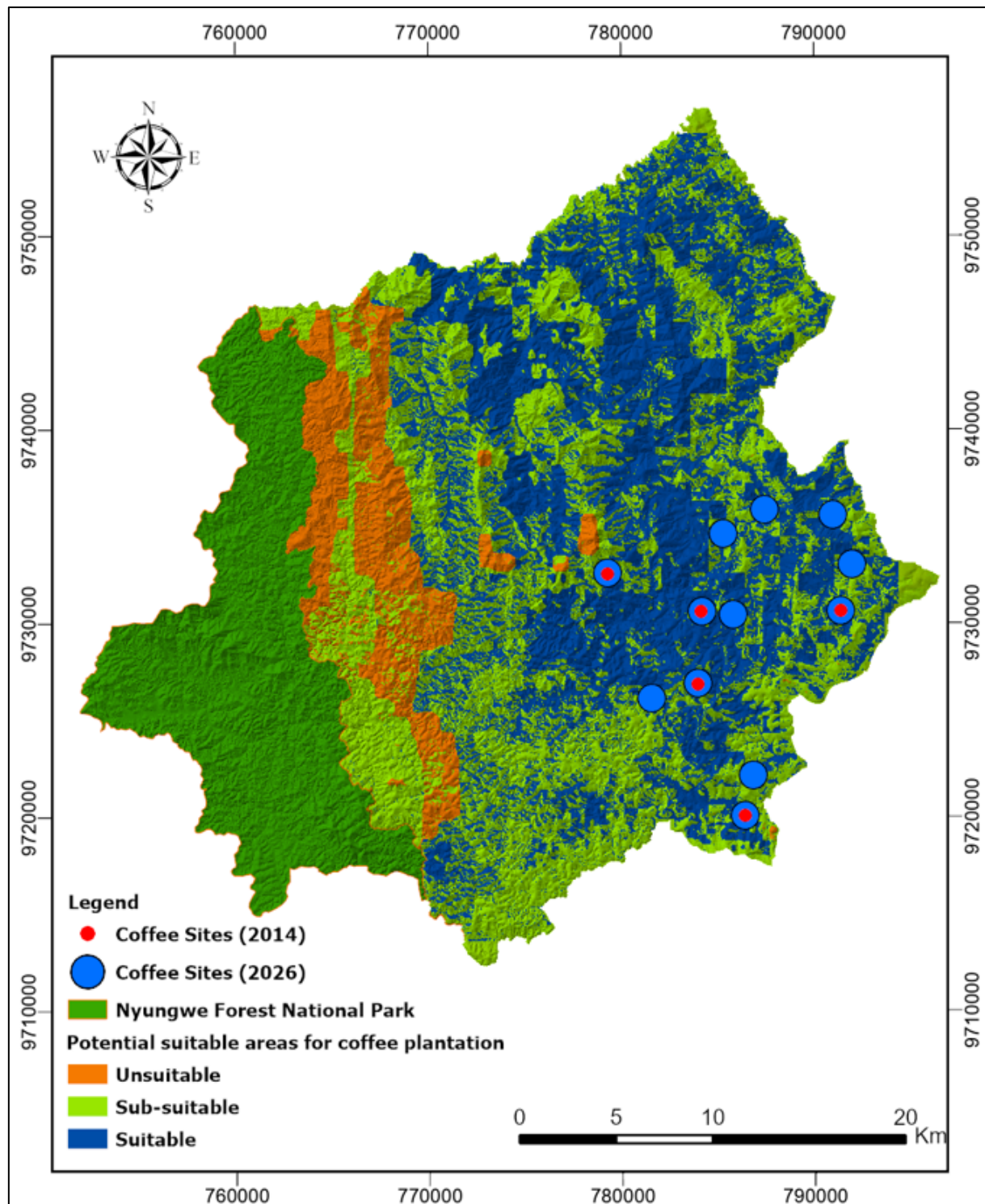


Figure 12. Map of the potential areas for coffee plantation under the baseline climate conditions (1970-2000).

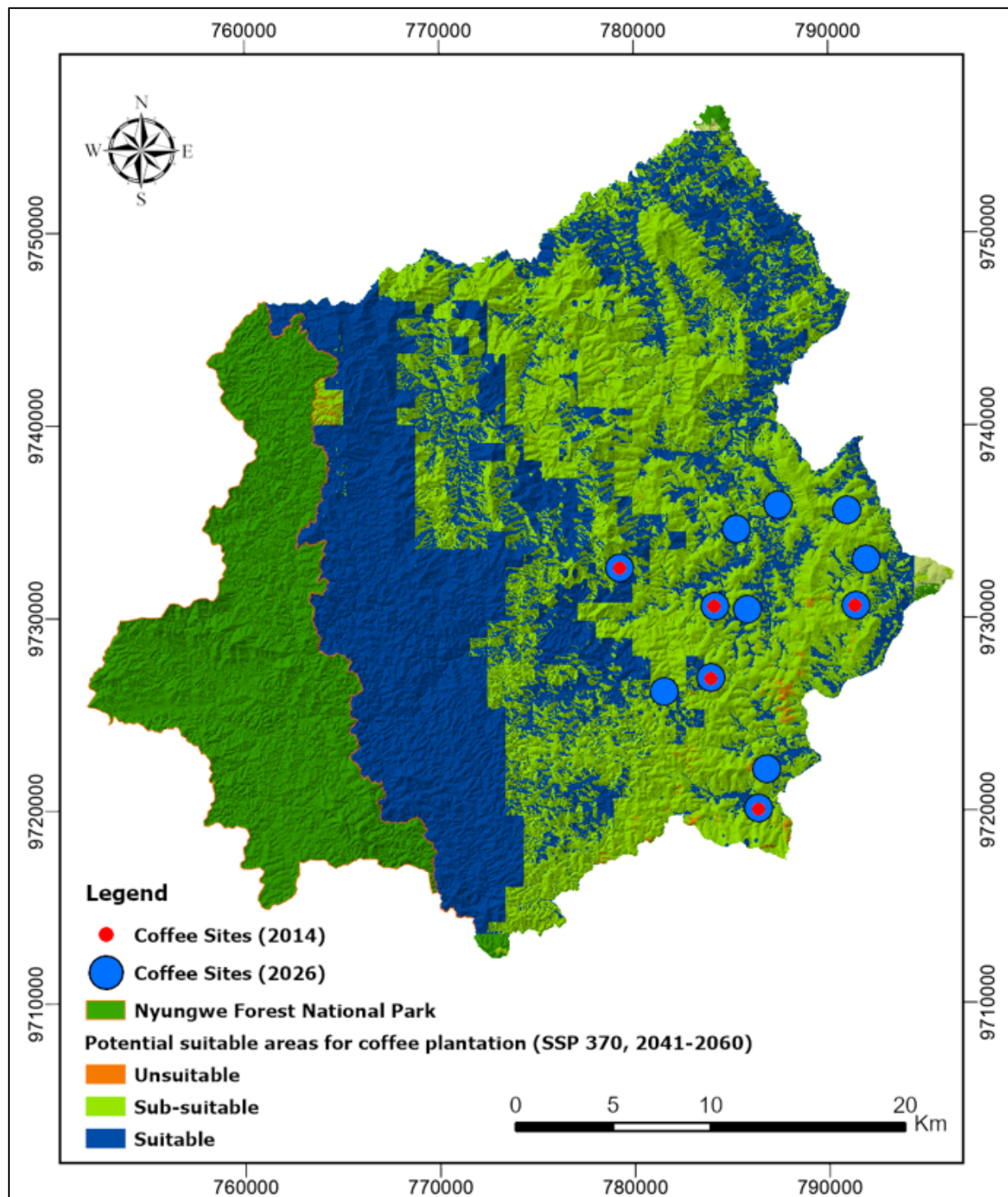


Figure 13 projects that coffee suitability will shift to higher elevation by 2060 under the SSP3-7.0 climate scenario.

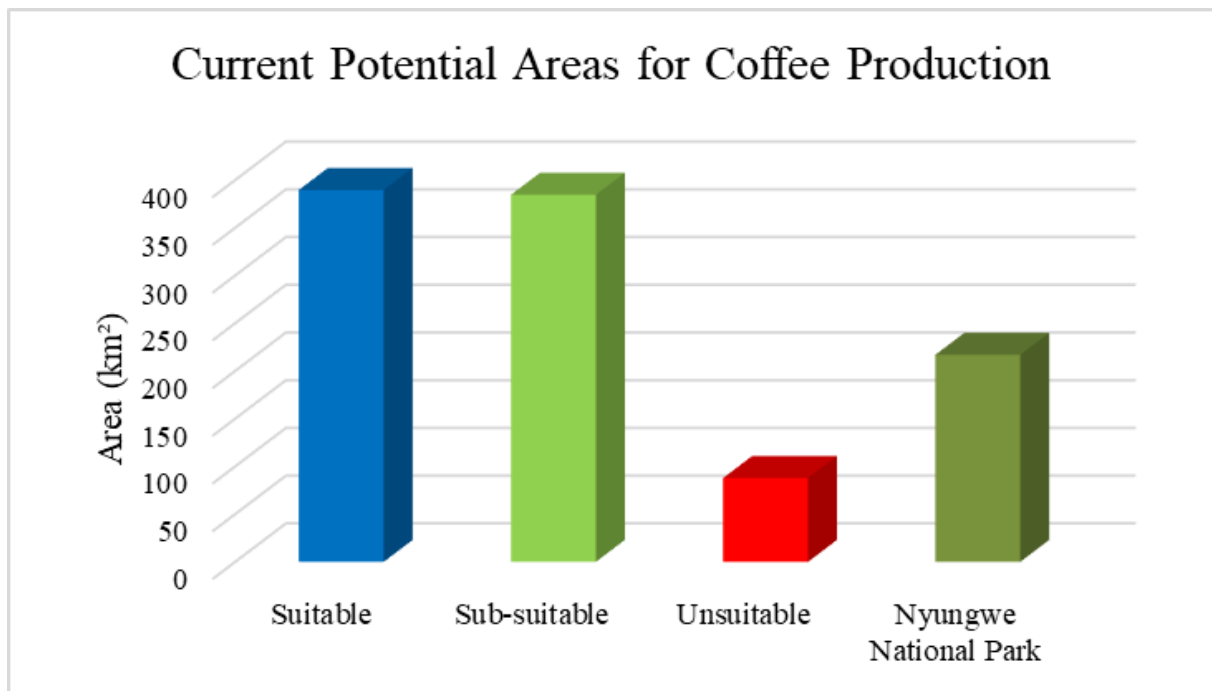


Figure 14a. Current potential areas for coffee production are based on historic bioclimate data.

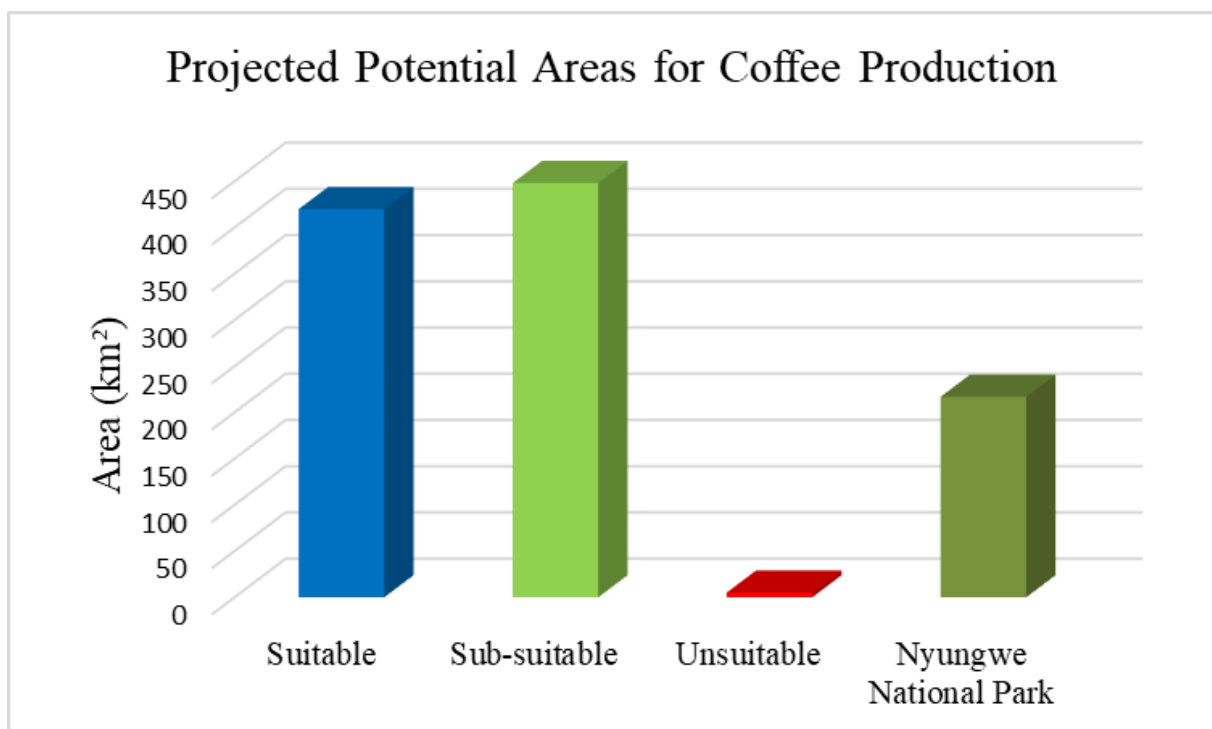


Figure 14b. Projected potential areas for coffee production under the SSP3-7.0 scenario for the 2041–2060 period.

5 Discussion

5.1 Suitability Criteria and Model

Results show that when overlaying the real coffee locations on the suitability map (Figure 12), all 12 sites are in the “suitable” and “sub-suitable” zones, with no sites falling into “unsuitable” zones. This suggests that the suitability model broadly captures the environmental and land-use conditions associated with existing coffee cultivation. The agreement between predicted suitability and real-farm locations indicates that the selected criteria (rainfall, temperature, soil pH, elevation, etc.) are relevant and correctly weighted. The AHP–GIS method is suitable for identifying where coffee can grow.

Since the AHP-based suitability model is a knowledge-driven weighted-overlay model rather than a statistical regression model, it cannot be validated with a simple R^2 in the same way as a fitted predictive equation as per Esri (2026a). R^2 is designed to quantify how much of the variance in an observed dependent variable is explained by a regression model with estimated parameters. In this study, however, the final suitability maps are produced by reclassifying criteria, assigning expert-derived weights, and combining standardized scores into a composite index. Because there is no directly modelled continuous response variable such as measured yield (Nzeyimana et al., 2014), and no regression function is fitted to observations, an R^2 value would not be meaningful indicator of model performance. The issue is therefore not only that R^2 is uninformative; rather, the structure of the AHP model does not provide the kind of statistical fit for which R^2 is intended (Malczewski, J., & Rinner, 2015). For that reason, Pearson correlation analysis was used as an exploratory tool to examine whether the relationships among environmental variables in Nyamagabe were consistent with ecological expectations, while the overlay of existing coffee sites on the final suitability map served as a plausibility check of the model output.

The topographic correlation analysis across Nyamagabe demonstrates that slope gradient exhibits a moderate-to-strong positive correlation with altitude ($r = 0.59$), indicating that the terrain becomes systematically steeper at higher elevations. Because Arabica coffee is commonly cultivated on steep hillsides, slopes exceeding a 25% gradient require targeted conservation management to avoid accelerated soil erosion. This topographic constraint supports regional environmental frameworks, which argue that the combination of high altitude and intense rainfall accelerates land degradation, ultimately limiting optimal production conditions (Nzeyimana et al., 2013; Roose & Ndayizigiye, 1997). Consequently, this spatial convergence aligns with sectoral reports by the ICO (2024), confirming a critical paradox: the district’s most climatically favorable highland zones are concurrently the most threatened by severe soil erosion, thereby risking a long-term decline in agricultural productivity.

Pearson correlation analysis also revealed a very strong negative relationship between precipitation and soil pH ($r = -0.87$). This highly significant negative correlation reflects the impact of accelerated soil leaching in the high-rainfall zones of Nyamagabe (Nzeyimana et al., 2014). As orographic precipitation increases, particularly in the western mountains near the Nyungwe forest, basic cations are systematically leached from the topsoil, resulting in heightened soil acidity (lower pH values). Concurrently, a strong positive correlation was found between elevation and SOM ($r = 0.78$). SOM accumulation is favored at higher altitudes in Nyamagabe, likely due to suppressed decomposition rates at lower temperatures and increased biomass production in high-rainfall zones. These findings reinforce the high suitability of higher-elevation zones for coffee cultivation.

Just like (Birhanu et al., 2024) highlighted, agricultural production zones, particularly for Arabica coffee, are moving to align with changing climatic suitability. Numerous crops are expected to shift their ranges. As illustrated in the projected suitability map (Figure 13), the extent of areas classified as fully suitable is expected to increase; some regions that are currently

ideal for growing coffee are expected to experience a decline in suitability. Conversely, a significant portion of land near Nyungwe National Park with higher elevations that was previously unsuitable for coffee production will become suitable. Climate projections for the 2041 -2060 period under the SSP3.70 scenario suggest a gradual upward shift in optimal Arabica coffee suitability, with higher-altitude regions becoming more favorable for production. This indicates that the long-term resilience of Nyamagabe's coffee sector may depend partly on a spatial shift toward elevated regions.

Elevation is considered the primary environmental gradient driving local climate variations in the study area. The Pearson correlation analysis (Table 6) reveals a very strong negative correlation ($r = -0.93$) between elevation and temperature, explaining the projected altitude shift. This relationship conforms to the environmental lapse rate, which in Nyamagabe aligns with the standard calculation of 0.6 per 100 meters of elevation gain. According to Wintgens (2004), specific temperature thresholds and their fluctuations dictate the physiological behavior and productivity of coffee trees. The sensitivity to extreme temperatures varies among species and individual plants. Furthermore, localized environmental variables such as wind speed and relative air humidity greatly influence how ambient temperature affects the crop. Consequently, under future climate scenarios (Figure 13), the geographic zone of optimal suitability migrates from east to west as cultivation shifts to higher altitudes to escape escalating baseline temperature.

Additionally, comparing elevation with precipitation reveals a strong positive correlation ($r = 0.75$), which confirms the orographic effect in the region (Hess & Tasa, 2014; Messerli & Winiger, 1992). This spatial trend explains why the western mountains near the Nyungwe forest exhibit a better suitability for future coffee production than the eastern lowlands, as the western windward zones receive significantly more rainfall. Conversely, a strong negative correlation was observed between temperature and precipitation ($r = -0.79$), indicating that warmer sites within the study area receive substantially less rainfall. This inverse relationship underscores that climatic suitability for *C. arabica* is highly sensitive to elevational gradients, leaving lower, warmer regions increasingly vulnerable to moisture deficits. Consequently, because the hottest zones are simultaneously the driest, the eastern part of the district faces a compounded climate threat (Nigussie et al., 2024; Ntawuruhunga et al., 2023).

These results align with previous studies and indicate that increased temperature is the main driver of the migration of current suitable areas. While both temperature and rainfall are critical, temperature appears to account for more of the projected reorganization of coffee suitability for two main reasons. Firstly, *C. arabica* has a very narrow optimal temperature range, even a 1°C or 2°C increase can push the plant out of its comfort zone, causing heat stress that leads to aborted flowers and smaller, lower-quality cherries (Hakorimana & Akcaoz, 2019). Secondly, warming is certain while rainfall is erratic. Global climate models agree much more on the direction of temperature than on the amount of rainfall (which may increase, decrease, or only become more erratic). Because warming is a consistent, global trend, it acts as a hard limit that physically shifts the coffee-growing belt toward higher, cooler ground.

Consequently, the results from the Pearson correlation matrix corroborate previous researchers, demonstrating that the topography actively interacts with multiple environmental factors to shape crop production. Topography influences local climate conditions, such as temperature and humidity, as well as the distribution of SOM, nutrient availability, soil texture, and other physical soil properties. These spatial variations in environmental conditions lead to differences in coffee performance across a landscape, making topography a key predictor of spatial variability in coffee yields.

However, the Pearson correlation confirmed a strong linear relationship between elevation and temperature; therefore, it is reasonable to intentionally constrain the weight assigned to elevation, thereby avoiding double-counting the same climatic influence (Malczewski & Rinner,

2015). Since Arabica coffee responds directly to thermal thresholds, temperature was assigned as the dominant weight to drive the biological boundaries. The restricted weights allocated to terrain, specifically 9.75% for elevation, 3.15% for slope, and 2.1% for aspect, ensure that topographic variables do not overpower the dominant climate data. Instead, these layers act strictly as minor topo-climatic modifiers to account for localized physical parameters that are inherently omitted by macro-climatic grids. Conversely, the results prove that the weights adopted from Nigussie et al. (2024) are reasonable for the established suitability model.

5.2 Implications for Sustainable Planning

A key implication of this study is that increased climatic suitability does not automatically mean that land is available or appropriate for coffee expansion. ICO (2024) notes that in Rwanda, climate risks undermine the coffee sector by reducing yields, elevating production costs, and increasing the vulnerability of smallholder households. Currently, national coffee yields exhibit substantial fluctuations across farms and provinces. Climate change exacerbates this volatility, rendering future production less predictable. This vulnerability is mainly driven by a low adaptation rate of shading techniques; nearly 44% of coffee farms completely lack canopy cover, which accelerates heat stress, reduces soil moisture retention, and heightens crop vulnerability during drought years. While shade trees have been shown to buffer ambient microclimatic extremes, active adaptation by farmers remains critically low. This lack of a thermal buffer is further amplified by aging coffee tree stocks, which structurally reduce baseline resilience to climate shocks. Overcoming these barriers requires targeted, proactive investments in regenerative practices, including systematic fertilization, pruning, and resource management interventions such as mulching, water-drainage infrastructure, hilling, and shade-tree establishment (ICO, 2024).

Supporting this perspective, Hakorimana et al. (2019) emphasized that climate change adaptation is vital to secure Rwanda's coffee production, which serves as a foundational economic pillar for the country. Operationalizing these strategies is further complicated by severe land fragmentation. ICO (2024) reports that approximately 30% of local smallholders distribute their coffee cultivation across three or more isolated parcels, severely restricting economies of scale and complicating land-use management. Because cherry productivity and bean quality are strictly dependent on stable localized climate conditions, insufficient adaptation and mitigation measures pose severe macroeconomic risks. To mitigate these threats, structural planning must prioritize agroforestry expansion, enhanced erosion control, and the implementation of land-use frameworks that respect environmental conservation boundaries (Nyamagabe District, 2024; FAO, 2026; SEI, 2024; Nzeyimana et al., 2013, 2014). Future coffee expansion should target investments toward accessible, biophysically suitable zones while strictly prohibiting agricultural encroachment into the protected fringes of Nyungwe National Park. Simultaneously, targeted technical and institutional support should be provided to farmers currently operating in marginal but active coffee zones to ensure their long-term viability.

These socio-institutional interventions are particularly urgent due to the physical geography of Nyamagabe. Mountain ecosystems are exceptionally sensitive to both historical and future climatic shifts due to their steep environmental gradients and rapid responses to atmospheric change. Nyamagabe District (2024) states that the vulnerability of mountain ecosystems along the Congo-Nile Divide is significantly amplified by the widespread replacement of native forests with intensive agricultural land uses, which has increased erosion, land degradation, and ecological instability. As Messerli and Winiger (1992) observed, these anthropogenic, man-made systems possess a significantly reduced buffering capacity, making them highly susceptible to even minor climatic fluctuations. Consequently, the inherent physical sensitivity

of the high-altitude divide, paired with a loss of ecological resilience, underscores the necessity for aggressive agroforestry and soil conservation measures.

Thus, the findings suggest that land suitability modelling can support strategic agricultural planning in Nyamagabe. However, successful climate adaptation will heavily depend on strengthening the resilience of existing farming systems through agroforestry, soil conservation, and improved farm management. Adaptation remains the most practical and economically efficient means for mitigating climatic impacts on smallholder agriculture. Ultimately, the successful deployment of these regional initiatives requires the formal integration of CSA frameworks into local district land-use policies (Kumar et al., 2026; Ntawuruhunga et al., 2023).

5.3 Limitations and outlooks for future studies

5.3.1 Limitation of AHP and Pairwise Comparison Matrix

Methodologically, suitability modeling for *C. arabica* can be categorized as knowledge-driven or data-driven approaches (Nigussie et al., 2024). This study utilizes AHP, a knowledge-driven method that relies on expert-defined weights and logical consistency. The AHP approach is particularly advantageous in complex landscapes like Nyamagabe, as it allows for the flexible integration of multi-criteria constraints—climatic, edaphic, and topographic, even when species occurrence data are limited. By prioritizing the structural consistency of expert judgments, the model ensures that local agronomic knowledge is central to the suitability output.

Kuo and Chen (2023) argue that a PC reflects an expert judgement, a subjective estimate based on the relative intensity of a compared entity. In a standard weighted overlay model, variable importance is often determined through subjective weight assignments, for instance, by assigning precipitation to a weight twice that of topographic slope. AHP makes this scientific use of PCM, and AHP calculates mathematically consistent weights (the Eigenvector). Then, it derives the weights for the weighted additive suitability model. While the final scores are quasi-interval and do not support R^2 testing, the use of AHP ensures that the subjective weighting of criteria is mathematically consistent, as verified by a CR of less than 0.10 (Malczewski & Rinner, 2015; Saaty, 2005).

Overall, this correspondence confirms the effectiveness of the selected AHP weights and thematic layers, as the model consistently reflects observed real-world patterns.

5.3.2 Sampling Sites and LULC

Fekadu and Andarege (2025) emphasize that access to granular, farm-level data allows for a more precise evaluation of suitability. A limitation of this study is the reliance on only 12 existing coffee sites for validation. While these sites demonstrate real-world relevance, they do not fully validate productivity or bean quality. The presence of coffee at a site does not necessarily mean optimal suitability, as the model does not account for yield data, farm-level management data, or parcel-level socioeconomic factors. Therefore, while validation against existing coffee sites provides an important plausibility check, it should not be interpreted as a full agronomic validation of productivity potential.

Esri (2026a) added that field observations are essential for identifying criteria, defining transformations, and validating model quality. In this study, the collected coffee sites data were used to evaluate the model and overlaid on the final coffee suitable map (Figure 12). The spatial overlay demonstrates that a majority of existing coffee sites align with suitable areas, while a portion of the areas belong to the unsuitable zones. It is observed that the active plantations fall within zones mapped as unsuitable regions, which are primarily driven by localized constraints within the slope gradient, soil texture, and LULC layers. This inconsistency is likely attributed to farm-level soil conservation and management practices such as localized terracing or organic

soil conditioning that are not captured by the coarse resolution of the baseline raster datasets. As for LULC layers, in this study, a validated 10-meter global land cover dataset was applied rather than the classification by combining raw imagery and field-derived land cover reference data. This approach provided a relative accurate, pre-classified, peer-reviewed data matrix (Venter et al., 2022), removing the risk of localized classification errors and allowing the model to focus strictly on multi-criteria suitability evaluations. As illustrated in Figure 1, the spatial overlay reveals that the 12 field sampling sites are equally split, with 6 sites intersecting the sub-suitable zones (characterized primarily by tree and rangeland covers) and 6 sites falling within the unsuitable tier (classified as built-up areas). Notably, no active sampling sites intersect the suitable cropland class. This pattern should not be interpreted to mean that rangeland is more suitable for coffee than cropland. In the model, cropland was deliberately ranked as the most suitable LULC class because it represents land that is already under agricultural use and is therefore more immediately available for coffee-based production. By contrast, rangeland and tree cover were ranked as sub-suitable because they may provide transitional land cover or ecological buffers for coffee agroforestry, but they are not assumed to be the optimal land-use class. The dominance of rangeland around the mapped coffee sites more likely reflects the fragmented smallholder landscape of Nyamagabe, where coffee is often grown in mixed agricultural mosaics, home-garden systems, or sparsely vegetated fields that a 10-meter land-cover product generalizes as rangeland or tree cover. It means that the Esri/Impact Observatory AI model might spectrally misclassify coffee systems as rangeland due to the unique way it blends grass, shrubs, and open canopies (Nigussie et al., 2024), although this global LULC map has an overall accuracy of 75% (Venter et al., 2022).

Therefore, the LULC result should be read as a representation of current landscape context rather than as direct evidence that coffee agronomically prefers rangeland over cropland. This result reflects the version of Nzeyimana et al. (2014), that in Rwanda, coffee always grows on the low fertility soil (see also Sect. 1.5). Cropland remains the preferred class in the suitability model, whereas rangeland indicates land that may already host dispersed coffee plants or offer potential for conversion into coffee agroforestry under appropriate management. This distinction is important because the observed overlap between coffee sites and rangeland is influenced by classification scale and local land-use heterogeneity, not by a reversal of the model's suitability ranking.

This distribution demonstrates that current smallholder coffee cultivation does not encroach upon intensive food croplands. Furthermore, the presence of active farms within areas mapped as built-up highlights the highly fragmented nature of the landscape, where smallholders plant coffee within rural residential compounds and home-gardens that fall below the macro-resolution threshold of the LULC data.

Additionally, while it is technically possible to convert certain land covers into coffee agroforestry systems, incorporating a LULC layer is vital to establish the real-world baseline constraints of the district. It acts as an environmental mask to prevent agricultural expansion into Nyungwe National Park (19.5% of the district) and built-up infrastructure. Agronomically and socio-economically, it prevents the model from recommending the conversion of vital subsistence food croplands, which would directly threaten local food security. Finally, LULC provides the baseline environmental context; planting coffee on steep, highly degraded bare land without assessing its current cover risks severe failure due to existing soil degradation and heightened landslide vulnerability.

Nzeyimana et al. (2014) explicitly state that land evaluation is essential to assess the opportunities and potential that a given parcel of land can offer for agriculture. However, the suitability modeler is based on raster cells, while decisions are based on other kinds of decision units, such as parcels or watersheds (Esri, 2026a). To align the raster-based suitability results with practical land management, a parcel-based aggregation approach should be adopted, as

recommended by Sohl et al. (Sohl et al., 2017). By utilizing zonal statistics (Malczewski & Rinner, 2015), the pixel-level data were summarized within cadastral parcel boundaries to calculate the mean suitability and the percentage of suitable area per parcel. This transition from pixel to parcel ensures that the suitability outcomes are directly applicable to local administrative decision-making units (Kilić Pamuković et al., 2023).

Finally, just like Nigussie et al. (2024) recommended, there is a critical need, incorporating machine learning methods to improve the selection of suitable areas for coffee cultivation, and for laboratory validations of edaphic factors. Machine learning algorithms demonstrate superior performance compared to traditional statistical modeling techniques when resolving complex, non-linear relationships among multivariate environmental and topo-climatic factors (Kumar et al., 2026). On the other hand, the use of LULC layer highlights the need for more detailed spatial data of the study area to ensure accuracy and feasibility. As this model primarily identifies biophysically suitable zones, it is important to distinguish between market and policy constraints, which dictate the legal and economic boundaries for expansion, and farm-level socioeconomic data, which determine the actual capacity of farmers to achieve optimal yields (FAO, 2007). Thus, although the model provides a useful regional overview, it should not be interpreted as a parcel-level recommendation tool in its current form. The spatial resolution of some datasets, particularly climate and soil layers, limits the precision of local interpretations. Future work would benefit from finer-scale field observations, parcel boundaries, and yield-related data in order to strengthen both validation and practical applicability.

6 Conclusion

This study assessed land suitability for Arabica coffee cultivation in Nyamagabe District, Rwanda, using a GIS-based multicriteria approach. It highlights the importance of land suitability evaluation as a pivotal tool for advancing sustainable agricultural planning, for regions such as Nyamagabe, which frequently lack extensive data and established modeling frameworks, the methodology used in this study is highly applicable. By integrating climatic, topographic, and socioeconomic variables, the model identified both current suitability patterns under baseline climate conditions (1970-2000) and projected future suitability patterns under the SSP3-7.0 scenario for 2041-2060 period.

The results suggest that coffee suitability is likely shifts spatially under climate change, with more favorable conditions moving towards higher elevation. The projected shift indicates a spatial redistribution of coffee suitability, suggesting that climate change may reconfigure where Arabica coffee can be cultivated within the district. Therefore, among all variables, temperature appears to be the most influential factor in explaining projected changes in suitability, which is consistent with previous studies. Temperature appears to explain more of the projected shift in suitability than rainfall, especially in highland districts such as Nyamagabe, which are sensitive to warming. The narrow thermal niche of Arabica coffee makes it vulnerable and highly sensitive to warming.

Although the total proportion of suitable land is projected to increase, several currently cultivated areas may experience declining suitability. Accordingly, these findings underscore the significance of combining spatial planning with climate adaptation measures. If the probability of ensuring the long-term viability of the coffee sector is to be improved, priority must be placed on enhancing the resilience of existing systems through agroforestry, soil conservation, and optimized farm management. Such site-specific adaptation endures as the most practical and efficient means of mitigating climatic impacts on smallholder livelihoods.

While the model provides a useful regional planning tool, future research should strengthen validation through finer-scale field data, diverse climate scenarios and models to systematically compare variations in suitability trends. Given the limitation of resolution, future land use and land cover (LULC) analysis requires field-based classification references for refinement. Furthermore, pairing the remote-sensing dataset with laboratory-verified soil samples and formal cadastral parcel datasets will bridge the gap between regional environmental modelling and actionable local administrative planning.

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APPENDIX I

Table A1. Comparison matrix, normalized matrix, and priorities of main factors, adopted from Nigussie et al. (2024).

A. Pairwise comparison matrix of main factors						
Coffee Potential	Climatology	Edaphic	Physiographic	Socioeconomic		
Climatology	1	5	4	5		
Edaphic	1/5	1	3/2	3/2		
Physiographic	1/4	2/3	1	2		
Socioeconomic	1/5	2/3	1/2	1		
Sum	1.65	7.33	7	9.5		
B. Normalized matrix of main factors						
Coffee Potential	Climatology	Edaphic	Physiographic	Socioeconomic	Sum	
Climatology	0.606	0.682	0.571	0.526	2.385	
Edaphic	0.121	0.136	0.214	0.158	0.629	
Physiographic	0.151	0.091	0.143	0.21	0.595	
Socioeconomic	0.121	0.091	0.071	0.105	0.388	
C. Priorities weight of main factors						
Coffee potential	Climatology	Edaphic	Physiographic	Socioeconomic	Sum	Weight
Climatology	0.606	0.682	0.571	0.526	2.385	0.60
Edaphic	0.121	0.136	0.214	0.158	0.629	0.16
Physiographic	0.151	0.091	0.143	0.21	0.595	0.15
Socioeconomic	0.121	0.091	0.071	0.105	0.388	0.09

Table A2. Comparison matrix, normalized matrix, and priority weight of the meteorological, edaphic, physiographic, and socioeconomic sub-factors (Nigussie et al., 2024).

A. Pairwise comparison matrix of metrological sub-factors					
Coffee Potential	Mean Annual Rainfall	Average Annual Temp	Annual Mean Min Temp	Annual Mean Max Temp	
Mean annual rainfall	1	2/3	2	3/2	
Average annual temp	3/2	1	3	2	
Annal mean min temp	1/2	1/3	1	2/3	
Annual mean max temp	2/3	2/3	3/2	1	
Sum	3.667	2.667	7.5	5.167	
B. Normalized matrix of metrological sub-factors					
Coffee Potential	Mean Annual Rainfall	Average Annual Temp	Annual Mean Min Temp	Annual Mean Max Temp	Sum
Mean annual rainfall	0.273	0.25	0.266	0.29	1.079
Average annual temp	0.409	0.375	0.4	0.387	1.571
Annal mean min temp	0.136	0.125	0.133	0.13	0.524
Annual mean max temp	0.182	0.25	0.2	0.193	0.825
C. Priorities weight of metrological sub-factors					

Coffee Potential	Mean Annual Rainfall	Average Annual Temp	Annual Mean Min Temp	Annual Mean Max Temp	Sum	Weight
Mean annual rainfall	0.273	0.25	0.266	0.29	1.079	0.27
Average annual temp	0.409	0.375	0.4	0.387	1.571	0.39
Annal mean min temp	0.136	0.125	0.133	0.13	0.524	0.13
Annual mean max temp	0.182	0.25	0.2	0.193	0.825	0.21
D. Pairwise comparison matrix of edaphic sub-factors						
Coffee Potential	pH	Texture	CEC	SOM		
pH	1	1.5	2	2		
Texture	0.667	1	1.5	2		
CEC	0.5	0.667	1	1.5		
SOM	0.5	0.5	0.667	1		
Sum	2.667	3.667	5.167	6.5		
E. Normalized matrix of edaphic sub-factors						
Coffee Potential	pH	Texture	CEC	SOM	Sum	
pH	0.375	0.409	0.387	0.308	1.479	
Texture	0.25	0.273	0.29	0.308	1.121	
CEC	0.188	0.182	0.193	0.231	0.794	
SOM	0.188	0.136	0.129	0.154	0.607	
F. Priority weight of edaphic sub-factors						
Coffee Potential	pH	Texture	CEC	SOM	Sum	Weight
pH	0.375	0.409	0.387	0.308	1.479	0.37
Texture	0.25	0.273	0.29	0.308	1.121	0.28
CEC	0.188	0.182	0.193	0.231	0.794	0.2
SOM	0.188	0.136	0.129	0.154	0.607	0.15
G. Pairwise comparison matrix of physiographic sub-factors						
Coffee Potential	Elevation	Slope	Aspect			
Elevation	1	3	5			
Slope	1/3	1	3/2			
Aspect	1/5	2/3	1			
Sum	1.533	4.667	7.5			
H. Normalized matrix of physiographic sub-factors						
Coffee Potential	Elevation	Slope	Aspect	Sum		
Elevation	0.652	0.643	0.667	1.962		
Slope	0.217	0.214	0.2	0.631		
Aspect	0.13	0.143	0.133	0.406		
I. Priority weight of physiographic sub-factors						
Coffee Potential	Elevation	Slope	Aspect	Sum	Weight	
Elevation	0.652	0.643	0.667	1.962	0.65	
Slope	0.217	0.214	0.2	0.631	0.21	
Aspect	0.13	0.143	0.133	0.406	0.14	
J. Pairwise comparison matrix of Socioeconomic sub-factors						
Coffee Potential	LULC	Distance to road	Distance to river			
LULC	1	3	3			
Distance to road	1/3	1	3/2			
Distance to river	1/3	2/3	1			
Sum	1.667	4.667	5.5			

K. Normalized matrix of socioeconomic sub-factors					
Coffee Potential	LULC	Distance to road	Distance to river	Sum	
LULC	0.6	0.643	0.545	1.788	
Distance to road	0.2	0.214	0.273	0.687	
Distance to river	0.2	0.143	0.182	0.525	
L. priority weight of Socioeconomic sub-factors					
Coffee Potential	LULC	Distance to road	Distance to river	Sum	Weight
LULC	0.6	0.643	0.545	1.788	0.6
Distance to road	0.2	0.214	0.273	0.687	0.23
Distance to river	0.2	0.143	0.182	0.525	0.17

Table A3. The following table shows the coordinates of the coffee sites from the NAEB website.

Objective ID	Sector	Coffee site name	X - coordinate	Y- coordinate
1	Kibirizi	RWACOF	29.56987	-2.43639
2	Kibirizi	KOAKAKA M.	29.55502	-2.43502
3	Cyamika	Gitega H. C.	29.62493	-2.41268
4	Cyanika	MIG Ngoma	29.61996	-2.43454
5	Gasaka	Bufcoffee R.	29.55332	-2.46834
6	Gasaka	Kigeme CWC	29.53176	-2.47522
7	Kibumbwe	MIG K.	29.51092	-2.41724
8	Mbazi	KOAKAKA G.	29.61589	-2.38957
9	Kibumwe	Bwenda M. C.	29.56497	-2.39871
10	Kaduha	Kaduha CWC	29.58402	-2.38744
11	Kamegeri	Mountain C. K.	29.57889	-2.51119
12	Kamegeti	Bufcoffee N.	29.57529	-2.52994

APPENDIX II

The following figures display the environmental variables in the study area. These include four thematic layers: climate, topography, soil, and socioeconomic factors. Data sources and spatial resolution are summarized in Table 1. The bioclimatic datasets: Annual Mean Temperature, Annual Precipitation, Max Temperature of the Warmest Month, and Min Temperature of the Coldest Month were downloaded from the WorldClim database. These included both the historical baseline (1970–2000) (Figure A1) and the future climate scenario (SSP3-7.0 under the 2041–2060 period) (Figure A2), all at a spatial resolution of 30 arc-seconds. Soil variables in Figure A3 are from SoilGrids at 250 m spatial resolution, including soil texture, pH, Soil Organic Carbon (SOC), and Cation Exchange Capacity (CEC). DEM-derived topographic variables (Figure A4) and river (Figure A5b) from the Rwanda DEM with a spatial resolution of 10-meters. The classification of LULC (Figure A5c) was extracted from the datasets, 2025 Sentinel-2 10m Land Use/Land Cover Time Series produced by Esri and Impact Observatory. Rwanda road data (Figure A5a) was downloaded from Humanitarian Data Exchange.

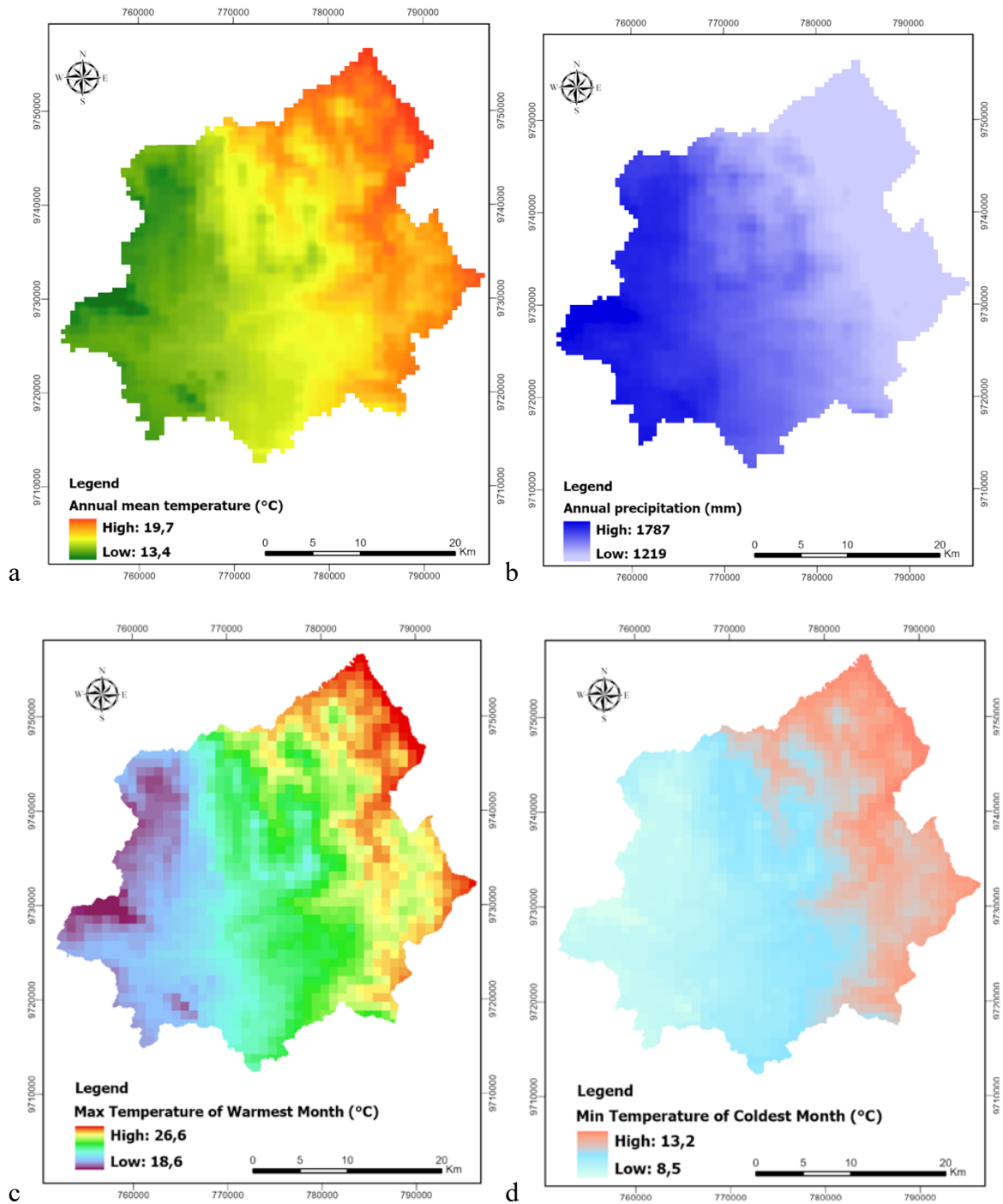


Figure A1. Maps of climatic thematic layers: a) annual mean air temperature; b) annual precipitation; c) maximum air temperature of the warmest month; d) minimum air temperature of the coldest month. In the WorldClim bioclimatic dataset, the warmest month and coldest month are determined directly from the monthly temperature layers. Under future climate scenarios, the timing and intensity of the warmest and coldest months will shift slightly as climate patterns evolve.

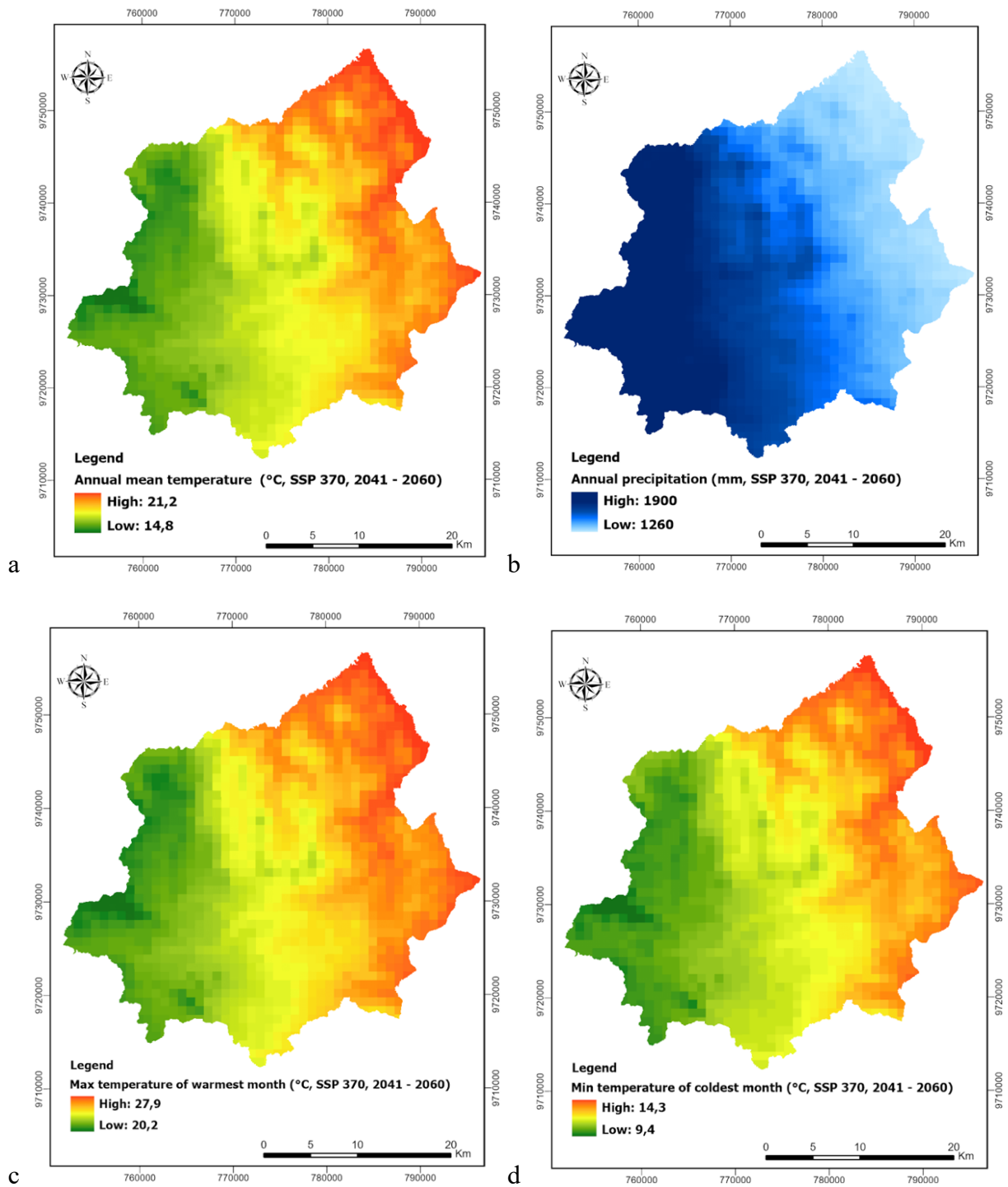


Figure A2. Maps of future climate scenarios SSP370 for the 2041 – 2060 period: a) annual mean air temperature; b) annual precipitation; c) maximum air temperature of warmest month; d) minimum air temperature of the coldest month.

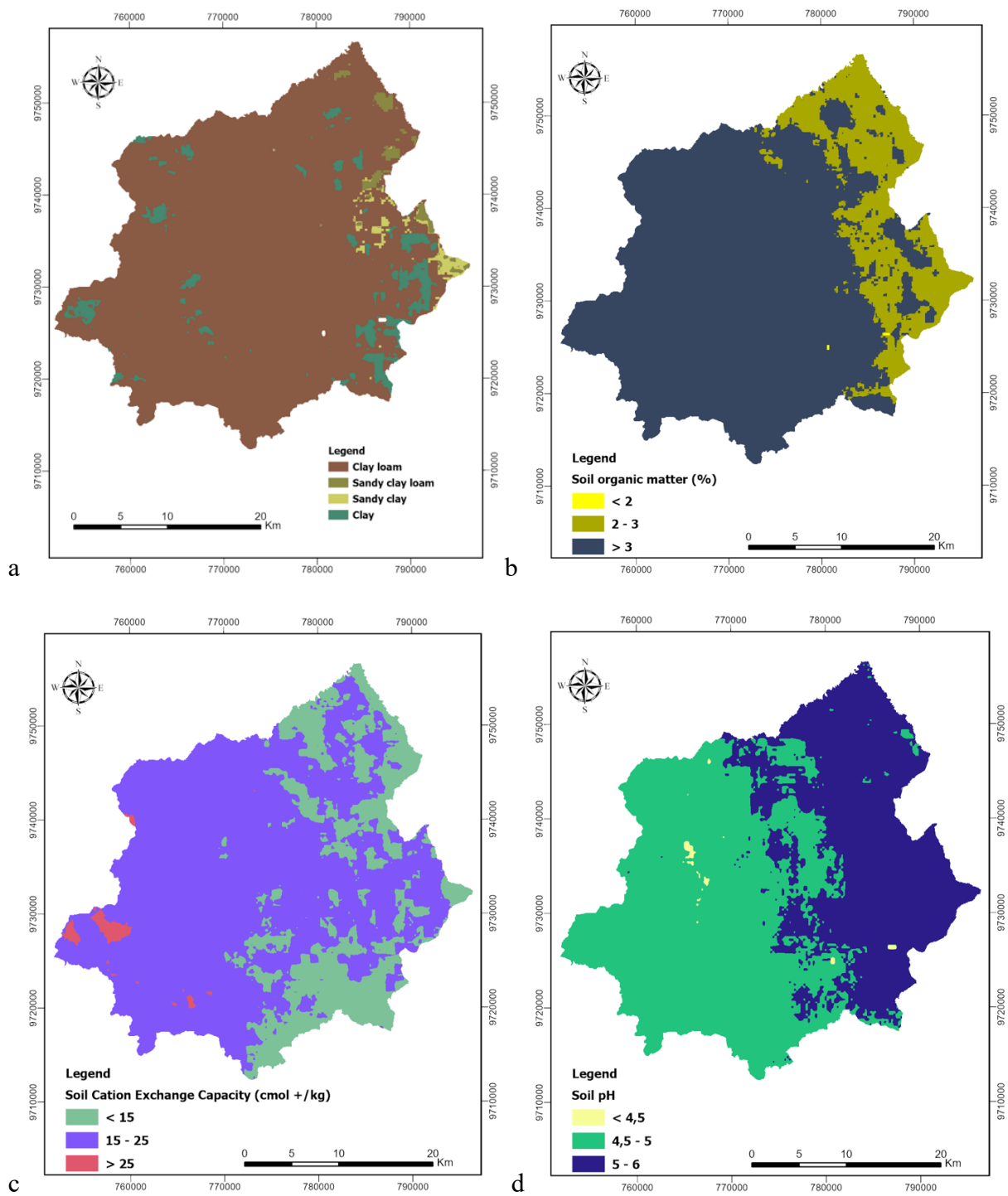


Figure A3. Maps of the distribution of the soil chemical and physical properties: a) soil texture; b) soil organic matter; c) cation exchange capacity; d) soil pH.

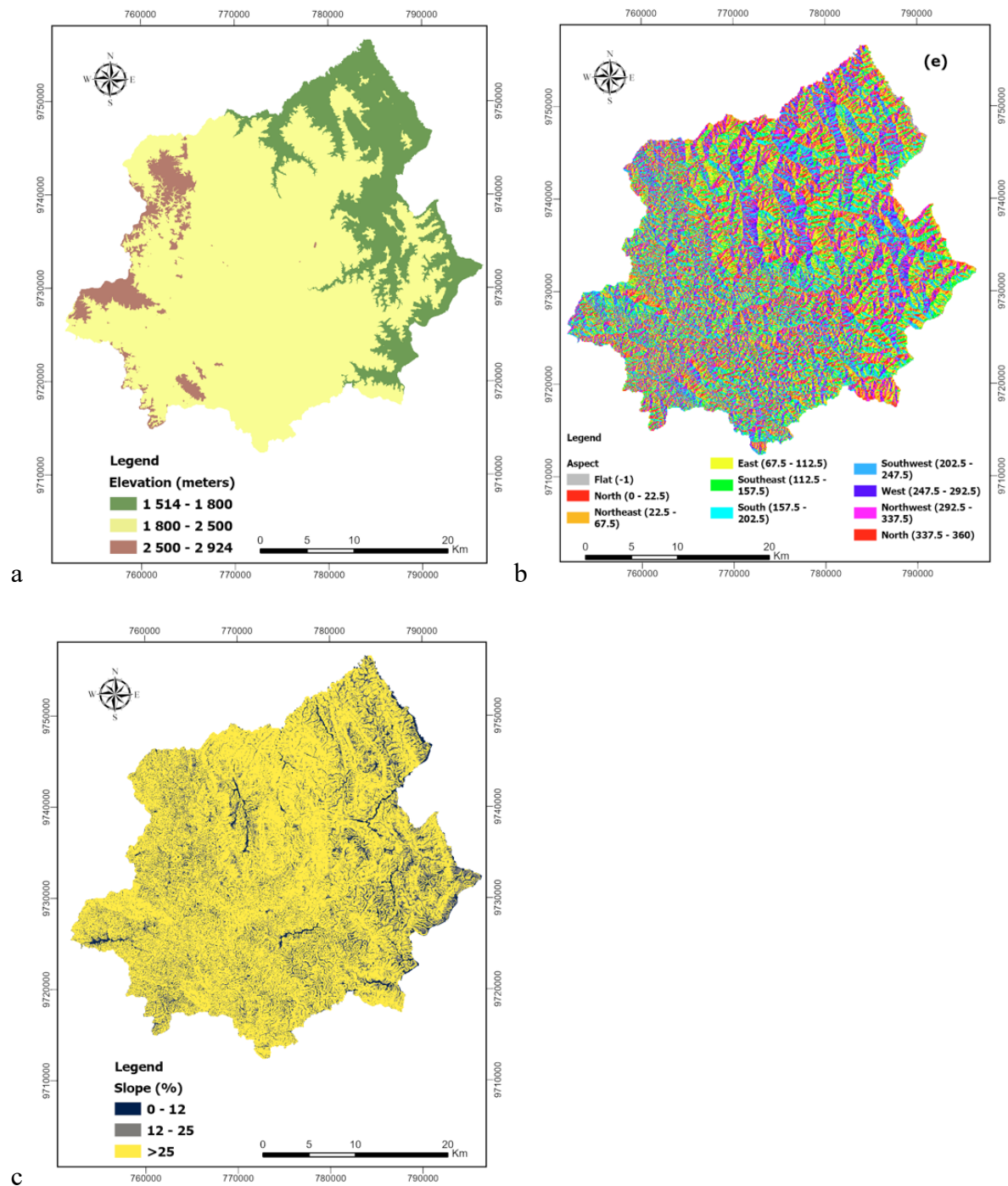


Figure A4. Maps of topographic thematic layers: a) elevation, b) aspect, c) slope.

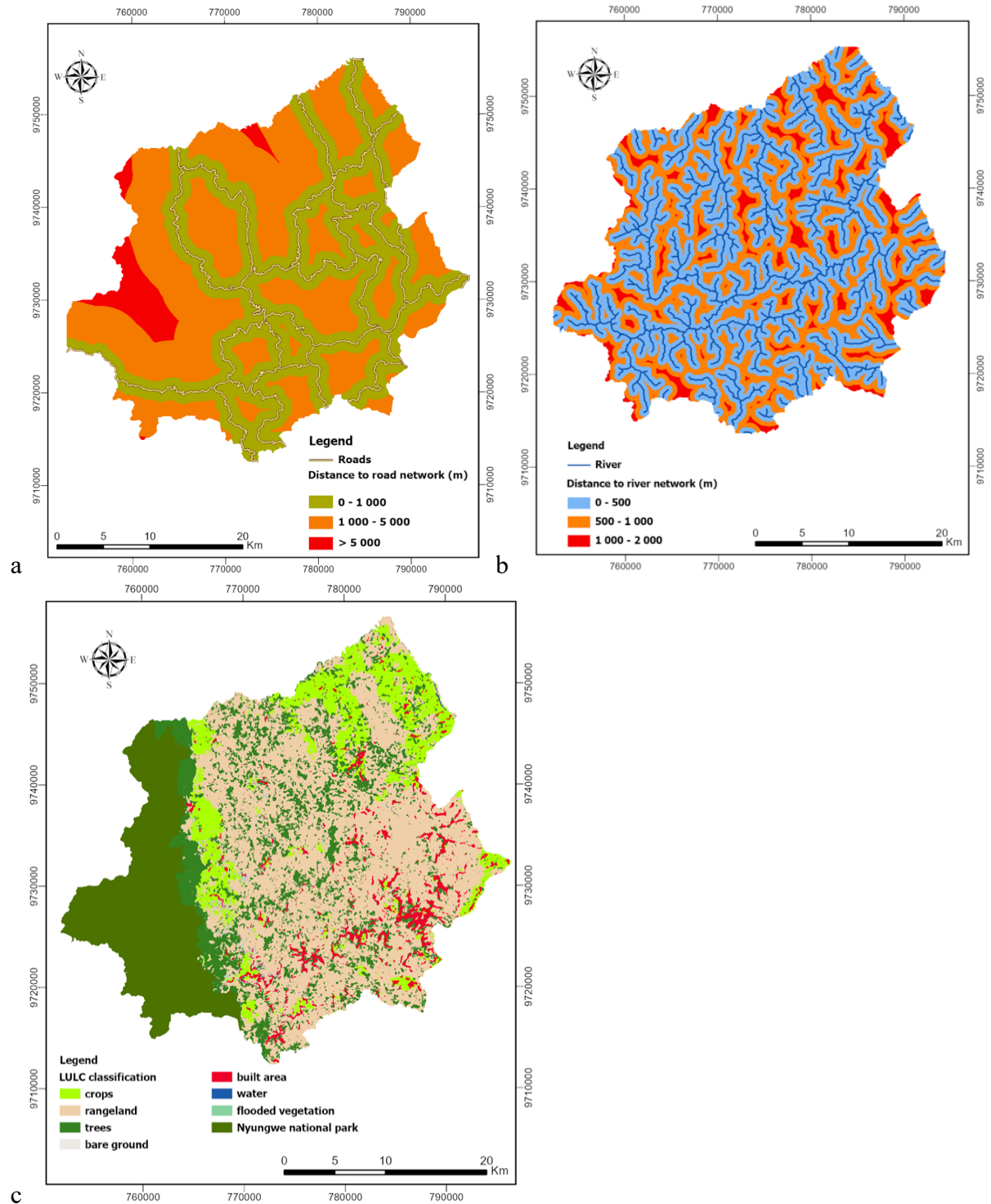


Figure A5. Maps of socioeconomic thematic layers: a) distance to road network, b) distance to river network, c) LULC classification.