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Geospatial characterization of climate-smart agroforestry in two contrasting physiographic zones of Rwanda

Donatien Ntawuruhunga[a,b,c,*], Edwin Estomii Ngowi[a], Halima Omari Mangi[a], Raymond John Salanga[a], Kelvin Mashisia Shikuku[c]

[a] *Department of Development and Strategic Studies, Sokoine University of Agriculture, P.O. Box 3000, Chuo Kikuu, Morogoro, Tanzania*
[b] *SACIDS Foundation for One Health, Sokoine University of Agriculture, P.O. Box 3297, Chuo Kikuu, Morogoro, Tanzania*
[c] *International Livestock Research Institute (ILRI), Naivasha Road, P.O. Box 30709-00100, Nairobi, Kenya*

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ABSTRACT

Efficient use of rich natural resources notably land, is one of the most important indicators of economic progress. The unmatched population growth with production has triggered increased demand for food. Nations have prioritized sustainable agriculture as a coping strategy. Climate-smart agroforestry (CSAF) can be one of the options to increase productivity, income, and food security, and stabilize the environment. CSAF denotes a practiced farming system of combining trees with crops or animals (AF) evolved in practices to enhance productivity and feed the food-insecure people while coping with the adverse effects of climate change. This study investigates the land suitability for CSAF in the Bugesera and Rulindo regions of Rwanda. Nine variables were considered for investigation in the study viz. elevation, slope, soil type, rainfall, temperature, LU/LC, distance from roads and trade centers, and landslide risks. The analysis used two commonly known techniques (AHP and GIS) integrated to classify and sort out the suitable land for CSAF practices and development. Results identified three CSAF suitability zones, ranging from 1,662.82 ha (1.60 %) as highly suitable and 90,123.78 ha (86.62 %) as moderately suitable to 12,262.50 ha (11.78 %) less suitable zones in Bugesera. In Rulindo, suitability zones range from 709.92 ha (9.69 %) as highly suitable and 6,514.56 ha (88.92 %) as moderately suitable to 102.24 ha (1.39 %) less suitable land for CSAF. Results further showed that the available means suitable land for CSAF are 34,683.03 ha in Bugesera (34,683.03 ± 48,304.71) and 2,442.24 ha in Rulindo (2,442.24 ± 3,539.79). Land suitability scores for CSAF largely varied across sites ($F = 1.33$, $p = 0.31$). Cross-validation using ground-truthing information (field visit and collection of GPS-based ground coordinates of random locations of actual CSAF) mostly supported the generated CSAF suitability maps (nearly 91 % of ground-based locations supported the model output). This study integrates GIS with AHP to plan CSAF farming and scaling up. In sites such as Bugesera and Rulindo where investigations on CSAF are scanty, these results reveal the extent of CSAF farming in the targeted areas. They can provide direction for future land use modifications, better land stewardship, and cost-effective solutions in study areas, and other agroclimatic zones. Moreover, this study will pave the way for further studies on the potential CSAF and possibly required interventions for the assessed areas.

1. Introduction

The changing climate and its devastating consequences are the biggest threat in our times. Rescue operations are underway in various parts of the world saving lives from natural disasters induced by climate change. Such effects are mainly falling primarily on the resource-poor and most vulnerable. Practicing modern agriculture involving tree-crop integrated farming can contribute to food security and safeguarding the environment. Climate-smart agroforestry (CSAF) was introduced to improve the old practices of tree on-farm farming practices with little knowledge of their impact on the environment, productivity, and rising global warming. So, CSAF evolved as a new practice of combining trees with crops that enhance agricultural productivity but also cope with the unstable climate.

Climate change is one of the biggest challenges of our times. Accordingly, FAO has placed climate change as one of its 14 themes in

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* Corresponding author at: Department of Development and Strategic Studies, Sokoine University of Agriculture, P.O. Box 3000, Chuo Kikuu, Morogoro, Tanzania.
E-mail address: donatien.ntawuruhunga@sacids.org (D. Ntawuruhunga).

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support of sustainable development. Subsequently, FAO initiated and developed climate-smart agriculture as a unified approach to addressing climate change challenges. The concept of climate-smart agriculture was 1st launched in the year 2010 by FAO in a background paper presented at the conference on agriculture, food security, and climate change held in the Hague (Everest, 2021). The approach is a momentum of actions aimed at transforming and reorienting agricultural systems to effectively support agricultural sustainability and ensure food resilience in an unstable climate. CSAF was added to this approach as a joint effort to improve agricultural productivity and address issues of food security to meet the needs of the growing population, decreasing arable lands, and biodiversity.

CSAF is the new name defining the age-old practice of raising trees together with crops within the contemporary challenges of climate change (Ntawuruhunga et al., 2023). CSAF involves modern farming practices (Aumeeruddy-Thomas and Michon, 2018) intended to increase production, and sustainable land use in addition to coping with the adverse climate shocks on the environment (Vilsack, 2021). CSAF practices include alley cropping, home gardens, silvopasture, taungya systems, and shelterbelts and windbreaks (Gold et al., 2000).

CSAF has the potential to contribute to sustainable development as admitted in global development summits, notably the United Nations Framework Convention on Climate Change (UNFCCC), the Convention on Biological Diversity (CBD), and the recent Africa Climate Summit (ACS) held in Nairobi (4–6 September 2023) where leaders were called upon to make ambitious pledges and commitments towards the adoption of a “Pledging and Commitment Framework”. Globally, CSAF has been a well-known smart farming practice among farmers, researchers, scientists, policymakers, and other farming practitioners (Raj et al., 2020). Globally and in low and middle-income countries (LMIC) specifically, experiences show that CSAF can contribute to sustainable rural development as a natural resource management best practice with proven positive impacts on the welfare of rural households (van Noordwijk, 2019).

In their study, Verchot et al. (2007) observed that CSAF is location-specific and comprises various models that can be adopted in varying physiographic zones due to differentiations in biophysical features, topography, soil types, availability of resources, rainfall, species natures, water availability, irrigation facility, farming practices, and prevailing climatic stresses. As to any new innovative practice, FAO (2013) added that barriers to the adoption and development of CSAF include its delayed return on investment and under-developed markets, emphasis on market-oriented agriculture, ignorance of the advantages of CSAF, the unclear status of land and tree resources, adverse regulatory frameworks, and lack of coordination between sectors.

In Rwanda, agricultural productivity challenges include high population density on limited resources. Such a situation has led to land fragmentation and reduced arable lands and farm sizes (>60 % of households cultivating <0.7 ha), over-cultivation of land with no fallow, soil erosion, intensive cultivation without restoration of soil nutrients, increased vulnerability to climate shocks (drought/heavy rains), as well as weak extension and research services (Republic of Rwanda, 2008). The misuse of agricultural fertilizers and agricultural chemicals has polluted water, and anthropogenic activities on wetlands have degraded and destroyed them.

In Rwanda, particularly in eastern savannah semi-arid lowlands prone to drought, characterized by traditional agricultural production practices and the progressive degradation of available natural resources, together with climate change, have caused devastating impacts on settlements, and increased poverty and food insecurity. Parts of the Bugesera and Rulindo regions have experienced natural disasters in recent times. CSAF can be one of the solutions for mitigating natural disasters and increasing agricultural productivity in those regions. However, enhancing the agricultural potential in these areas requires baseline information scientifically proven on their agroclimatic conditions, and biophysical and socioeconomic characteristics. In a recent report on population published by the National Institute of Statistics of Rwanda (2023), the population is currently estimated at 13,246,394 on a surface area of only 26,336 sq km.

Despite efforts by Rwanda to cope with the rising food insecurity in the country, limited resources, and unreliable agricultural techniques, have been alarming largely due to the low level of agricultural production that has never matched the rapid population growth (Pender et al., 2006; Himeidan and Kweka, 2012). For sustainable land use on limited arable land, deliberate land management strategies and tools need to be urgently identified, analyzed, and promoted (Iiyama et al., 2018).

In modern agriculture, the use of remote sensing, geographic information systems (GIS), and global positioning systems (GPS) have become integral and powerful tools for field analysis and map generation for modernizing farming practices. In this modern era, scientific and technological advances in remote sensing and GIS have revolutionized the process of collecting data on agricultural characteristics, such as biophysical (altitude, soil, climate, LU/LC) and socioeconomic data. This study mapped and analyzed the physical features of potentially suitable lands for CSAF in Bugesera and Rulindo using available geospatial information (GIS and remote sensing) to determine the highly suitable areas for CSAF.

By identifying, accessing, gathering, and analyzing geospatial data, it is possible to discern areas with high potential for CSAF, assess the productivity and sustainability of different CSAF practices, and determine barren land areas and those that are prone to hazards. Results can be used to develop targeted interventions that promote sustainable land use, increase food security, and constitute a tool for end-users in the field in limiting unexpected disasters on farms. CSAF constitutes a novice in modern farming, hence there exists limited literature on land evaluation for various CSAF practices using RS and GIS (Ayehu and Besufekad, 2015).

On the other hand, Feizizadeh and Blaschke (2012) conducted research in Tabriz (Iran) for agriculture suitability analysis with the help of weighted overlay analysis based on GIS and analytical hierarchy process (AHP) techniques on soil information (soil fertility and soil pH data), topographical information (elevation, slope and aspect data), climatic information (rainfall and temperature data) along with groundwater information.

It is obvious that the process of finding suitable sites depends on different variables or criteria. These criteria have a different level of importance informing many different techniques to be used to determine the weights of these criteria. It is up to researchers’ concern to decide on how to combine different datasets to form a single index (Hassan et al., 2020). The AHP multicriteria decision-making technique for suitability analysis was introduced by Saaty (1980). In a pairwise comparison matrix, AHP calculates the weights of criteria based on experts’ opinions and local knowledge (Cools et al., 2003). According to Malczewski (1999), the integration of multicriteria decision-making (MCDM) and GIS methods is more practical and useful compared to standard map overlay methods in numerous applications. Application of AHP in integration with GIS has been extensively used by scientists in different fields to assess land suitability for many crops, e.g., Kihoro et al. (2013) assessed the suitability of sites of rice crops using GIS and AHP techniques. On the other hand, Feizizadeh and Blaschke (2012) integrated GIS with AHP techniques to identify the land resources for agricultural production. Furthermore, in Bangladesh, Muhsin et al. (2018) evaluated land suitability for agriculture and industrial sites using GIS and AHP techniques. Additionally, Muhsin et al. (2018) evaluated the ecological capability to support the tourism industry in mountainous areas of Iran using the integration of GIS and AHP techniques.

Other techniques have been tested to determine the weights of these criteria, such as the parametric method (Albaji et al., 2009), the ordered weighted mean (Mokarram and Aminzadeh, 2010), the Electre Tri (Mendas and Delali, 2012), the membership approach (Ahamed et al., 2000; Cengiz and Akbulak, 2009), relational analysis, simple overlay maps in ArcGIS (Kuria et al., 2011; Falasca et al., 2014), regression-based analysis and Principal Component Analysis (PCA) (Elsheikh et al., 2013) as well as the FAO framework. However, these techniques have drawbacks in determining criteria weights (Chuma et al., 2021). The FAO 1976 framework remains a widely utilized method in land suitability evaluation (Elsheikh et al., 2013; Ahmad et al., 2017; Feizizadeh and Blaschke, 2013).

To our knowledge, no study to date has been conducted in the two separate physiographic zones of Bugesera and Rulindo of Rwanda to investigate the extent of CSAF and its potential on land sustainability, environmental viability, and food security. Some of these unexplored issues appear to be important and worthy of investigation in the context of recent world food price spikes and anthropogenic climate change concerns (Jamnadass et al., 2013), the challenge of a growing global human population, decreasing arable land, decreasing biodiversity and effects of climate change in various parts of the world.

In this study, we used GIS and AHP approaches to estimate the land suitability potential for CSAF in the Bugesera and Rulindo regions as a case study for its scale-up under different agroecological zones. The main objective of this study was to assess the potential land suitability of the two separate zones for CSAF farming by considering the different factors inherent to land suitability. The specific objective of this study was to investigate suitable land for CSAF across the Bugesera and Rulindo zones. It was hypothesized that suitable lands for CSAF vary with the region's biophysical, climatic, and socioeconomic factors (Nath et al., 2021). This study integrates GIS with AHP to plan CSAF farming and upscale. In sites such as Bugesera and Rulindo where investigations on CSAF are scanty, these results reveal the extent of CSAF farming in the targeted areas. They can provide direction for future land use modifications, better land stewardship, and cost-effective solutions in Bugesera-Rulindo, and other agroclimatic zones. Moreover, this study will pave the way for further studies on the potential CSAF and possibly required interventions for the assessed areas.

2. Materials and methods

2.1. Study area

The study area lies on two separate physiographic zones of Rwanda namely, Bugesera and Rulindo. Rwanda is located in East Africa and shares its borders in the west with DR. Congo, north with Uganda, east with Tanzania, and south with Burundi (Fig. 1). Rwanda covers an area of 26,338 sq km, largely dominated by highlands, followed by river valleys; while the altitude ranges from 920 to 4486 m a.s.l. (Li et al., 2021). Its population is estimated at a population of 13,246,394 (NISR, 2023) with 72.1 % living in rural areas.

According to Fairclough (2020), the geology of Rwanda encompasses the Mesoproterozoic metasediments, largely comprised of sandstones alternating with quartzites, sandstones, and shales, which are all assigned to the Mesoproterozoic Burundian Supergroup that are sometimes locally intruded by granite. Older granites along with granitic-gneisses and migmatites of the Palaeoproterozoic age are predominating in the eastern part of the country whereas the Neogene volcanics, ranging in age from Cenozoic to recent, predominate in the northwestern and southwestern parts of Rwanda. Alluvium and lake sediments of the Quaternary age occur in parts of the western rift and along the rivers and lakes throughout Rwanda. In addition, other parent materials that occupy more than 1 % of the total country's area are basic rocks, basaltic (calcareous) rocks, volcanic ejecta, and lava (Verdoodt and van Ranst, 2003). Elsewhere, soils derived from volcanic, basaltic, and calcareous materials offer favorable soil property conditions for crop production and development.

The geology of Rwanda, Burundi, and southern Uganda are quite similar. The oldest rocks of Rwanda are migmatites, granitic-gneisses, and mica schists of the Paleoproterozoic Ruzizian Basement overlain by the Mesoproterozoic Kibaran Belt (Fairclough, 2020).

Geomorphologically, the landscape of Rwanda is typically diverse with different disparities of slopes. The alluvial plains and plateaus are relatively flat, with slope gradients ranging from 0 to 6 % (Republic of Rwanda, 2020), the steepness of the valleys varies from 6 to 13 %, whereas the landscape of thousand hills (nickname given to the scenic small nation) is characterized by slopes varying between 13 and 25 %.

Regarding soil types, Rwanda's soil pattern is quite complex due to the complexity of the origin parent materials (geology and geomorphology), topography, variability in altitude and climate, drainage conditions, soil depth, and soil texture (Republic of Rwanda, 2020). These factors have accordingly influenced differences between the major soil types in terms of soil chemical and physical properties.

As described by the Republic of Rwanda (2020), 10 % of the soils of Rwanda are fine clayey with > 60 % clay content — these soils are developed on the old volcanic materials of the Impara agroecological zone; the Vertisols of the eastern valleys are also characterized by a clay content over 60 %. 70 % are clayey with a clay content varying between 35 and 60 %. 17 % are loamy soils with between 20 and 35 % clay — these soils are developed on granite or shale intervened by quartzite

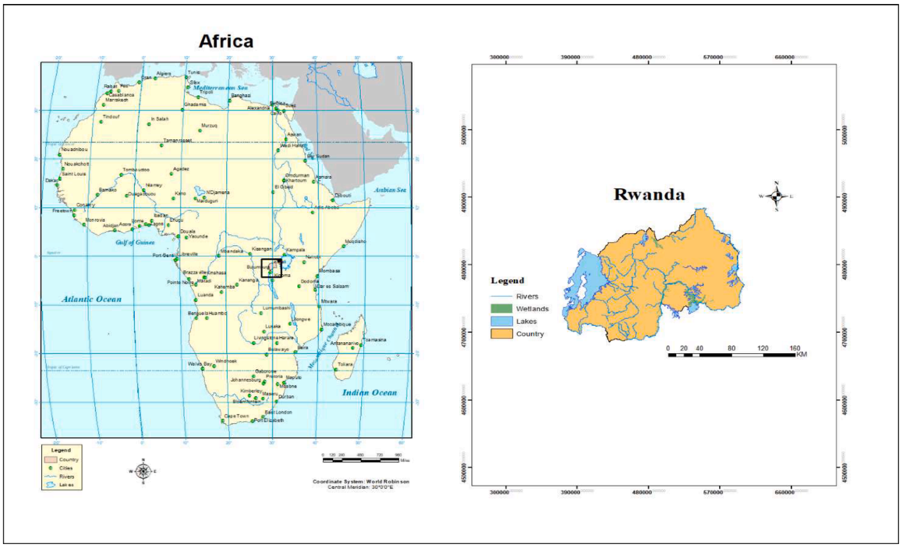

Fig. 1. Geographical location of Rwanda (adapted after CGIS).

material; only 3 % are organic soils; sandy soils (with less than 20 % clay) are very rare (less than 1 %) (Verdoodt and van Ranst, 2003). Table 1 shows the aerial extent of the texture classes of the soils of Rwanda.

Bugesera is located in the Eastern savannah semi-arid lowland zone between Latitude 1°37′56″ S and 2°13′9″ S and Longitude 29,^{0}21′0″ E and 30,^{0}18′0″ E. It covers an area of 1337 sq km (Fig. 2). The average temperature oscillates between 26 and 29 °C. The elevation varies from 1100 to 1780 m from the mean sea level. The average annual rainfall is 943 mm. The vegetation is largely dominated by the savannahs' shrubs and acacia trees.

Rulindo is located in the Temperate zone of the Central Highlands between Latitude 1°44′S and Longitude 29°59′E and is mostly characterized by mountains. Rulindo has an area of 567 sq km (Fig. 2). The area has steep slopes with an elevation of 1470–2200 m. The vegetation is largely composed of food crops on hillslopes and valleys with woodland eucalyptus, grevillea, and calliandra. The mean annual temperature is 19 °C., while the mean rainfall is 1243.3 mm p.a.

2.2. Methodology framework for CSAF land suitability assessment

We extracted the input variables (FAO, 2007) from different datasets which we then reclassified, ranked, and integrated by the weighted overlay (WO) technique in the GIS environment to produce the sub-models of the CSAF suitability of each variable. The process followed in this study is illustrated below (Fig. 3).

Basically, variables of interest were selected based on their importance and significance in farming systems, and nine different variables were picked to fit the purpose. Further, we used the AHP to estimate weights for each considered variable, and then we adopted the weighted overlay method to generate the land suitability maps for CSAF.

2.3. Assessment of CSAF land suitability in study areas

In this study, we chose nine individual suitability variables for the geospatial characterization of CSAF in the study area: elevation, slope, soil type, rainfall, temperature, LU/LC, distance to roads and trade centers, and landslide risks (Table 2). Before variable determination, we extensively consulted the literature (Dawit et al., 2020) and visited some parts of the study area as a pilot survey. Then, these were mapped using GIS. The information involved digitized and tabulated data collected from the center for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda (Table 2).

2.4. Selection of evaluation criteria

According to Kihoro et al. (2013) and Prakash (2003), the specified criteria must guide the eventual outcome and highlight the decision-making environment. A multi-criteria assessment technique was performed to determine land suitability, and its criteria used geographical, non-spatial, qualitative, and quantitative data (Chen et al., 2010). This study analyzed four primary (topography, soil, climate, socioeconomic) and nine criteria (elevation, slope, soil texture, rainfall, temperature, LULC, distance to road, distance to trade centers, and landslide risks). The parameters were chosen after reviewing crop-tree integrated farming literature and consulting experts in this field.

Table 1
Aerial extent of the texture classes of the soils of Rwanda.

Soil texture class (% clay)	Area (Km^2)	Area (%)
Fine clayey (> 60)	2378	10
Clayey (35 – 60)	16,193	70
Loamy (20 – 35)	4086	17
Sandy (<20)	22	<1
Organic material	807	3
Total	**23,486**	**100**

Source: Adapted from Verdoodt and van Ranst (2003).

Topography: Topography is made up of elevation and slope. These factors affect agricultural land suitability for plant growth and must be taken into consideration during suitability assessment.

Geomorphologic formation characteristics are intimately linked with soil formation (Yanos and Udan, 2022). The core aspect for determining soil erodibility and landslide risk is the slope gradient (Koulouri and Koulouri, 2007). Slope gradient is a very important factor affecting soil erosion intensity and landslide intensity. On the other hand, an increase in slope degree delays soil formation and reduces soil depth and fertility (Fox and Rorke, 1999).

The elevation affects agricultural land due to temperature changes in altitude and differences in plant cover (Yanos and Udan, 2022). For every increase of 100 m in elevation gain on the mountains, the seasons of vegetation and bloom are postponed by 4–6 days. This information affects farmers' choices for the agricultural plant species to adopt.

Soil properties: The selection of "which crops to grow where" and other associated crops is based on information from land evaluation for farming purposes (Yanos and Udan, 2022). Soil reaction is the acidity or alkalinity generated by a chemical, mineral, or biological environment (Yanos and Udan, 2022). Most importantly, pH affects soil fertility and plant nutrition. Hence, the adjustment and maintenance of soil acidity is paramount for the management of acidic soils to increase crop production using different approaches (mechanisms/techniques) (Ameyu, 2019).

When choosing soils for agrarian purposes, the depth of the soil that can be used by crops is also of paramount importance (Yanos and Udan, 2022). To some extent, according to expertise, many irrigated crops give great yields with a well-drained effective root depth of 90 cm.

Another crucial aspect of soil is texture. The majority of the soil's physical and chemical features are influenced by its texture class (Mustafa et al., 2011). Soil texture affects water infiltration, retention, nutrient absorption, aeration, tillage, microbiological activity, and irrigation (FAO, 2004). Soil texture is a natural, untreated soil property (Yanos and Udan, 2022). Soil texture was considered in the criteria.

Agroclimatic conditions: One of the main variables impacting plant growth is precipitation (rainfall) (Yanos and Udan, 2022). Typically, 400 mm of precipitation per year is regarded as ideal for the growth of plants (Jafari and Zaredar, 2010).

Extreme temperatures are of utmost importance for forecasting thermal consequences on our planet (Yanos and Udan, 2022). This variable is important in the treatment of living things, as well as in the production of food, beverages, and agriculture. Subsequently, these two variables were utilized in this analysis.

Land use: In Rwanda, land stewardship is in conflict with land conversion in areas of urbanization, roadways, modern village settlements, and agricultural modernization (Ntawuruhunga and Twahirwa, 2023) but in compatibility with forestry and CSAF (in condition of compliance with management and control principles).

Land cover: Some of the most important factors affecting the land suitability classification for CSAF development are built-up areas, closed agriculture, forest plantations, irrigation, natural forests, open agriculture, and open land. Whatever land is favorable for population settlement and forest development will definitely have more suitability for CSAF land use.

Distance from roads and trade centers: Considering villagers' main occupation (farming), places are suitable for farming where in addition to having biophysical factors are not far away from roads (feeder roads) and trade centers due to easier transportation of farms harvests from villages to sale.

Landslide risks: Terrain conditions at high and very high risk prone to natural hazards such as landslides are hostile to human settlements and farming and are left for other landscape developments, management, and control such as protected areas or ecotourism development areas.

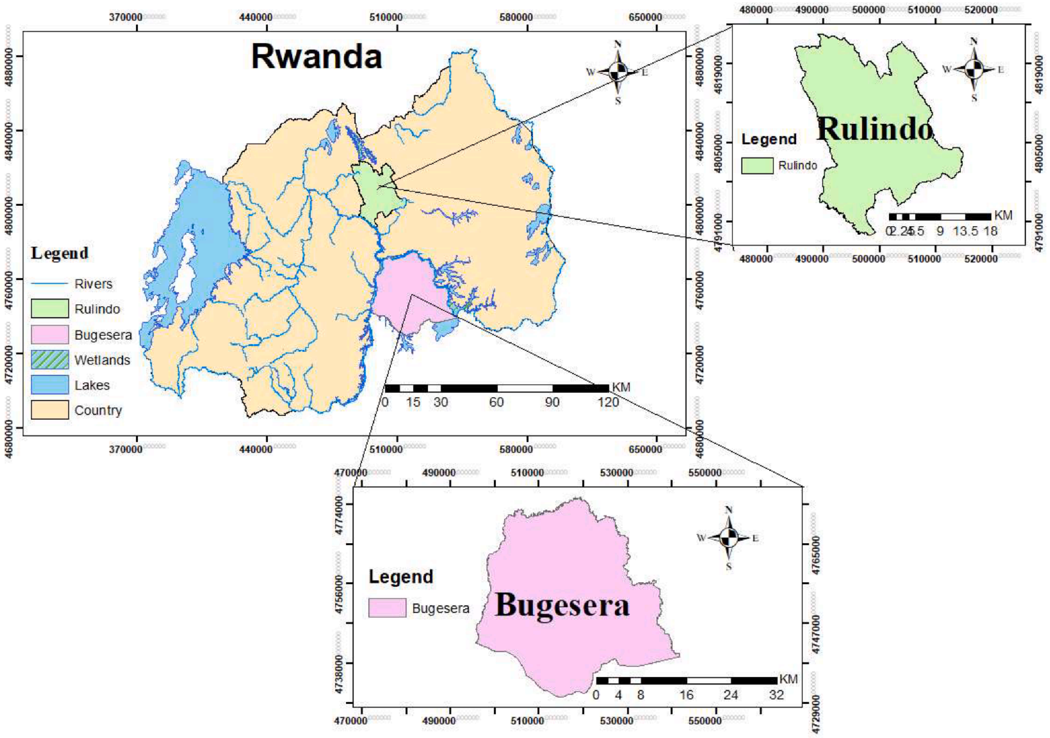

Fig. 2. Location of field study (Bugesera and Rulindo: adapted after CGIS).

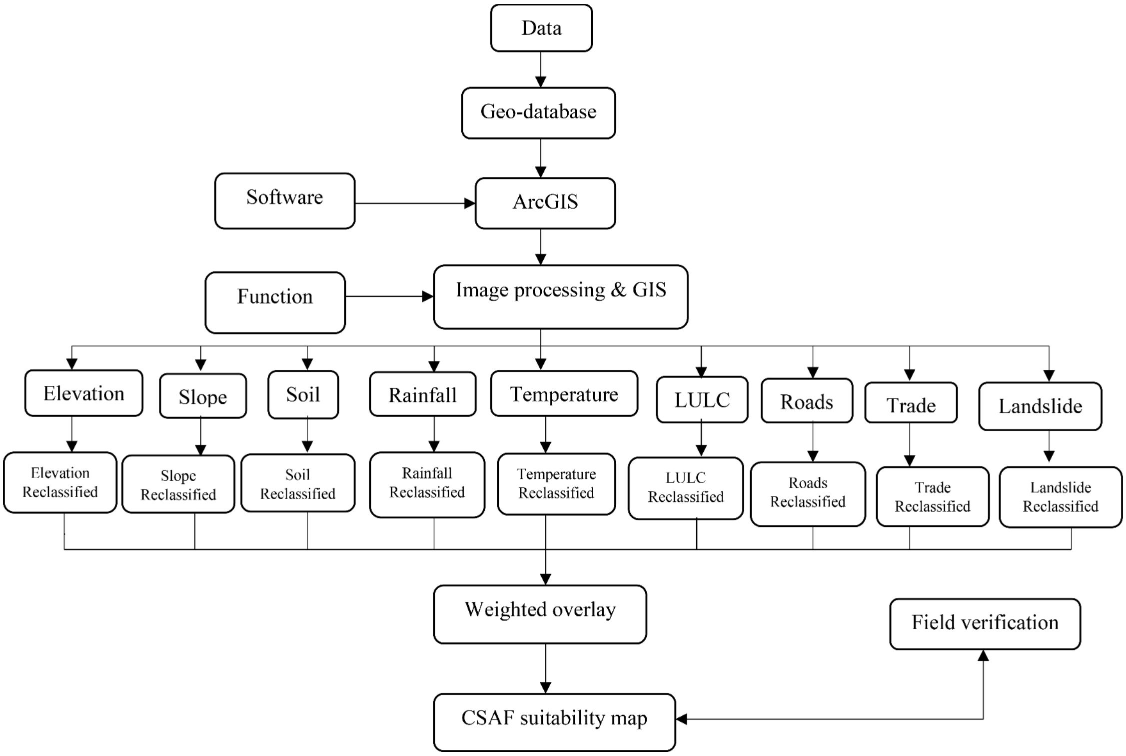

Fig. 3. Methodology workflow.

2.5. *Factor mapping using GIS*

This step involved the use of digitized and tabulated data collected from the center for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda. In this study, nine variables were gathered and utilized. These included shapefiles of administrative boundaries, roads, and trade centers. Equally used data included satellite images which comprised the Digital Elevation Model (DEM) with a resolution of 30 m and a digital agroclimatic database containing soil types, temperatures, rainfall, LU/LC, landslide risks, and agroclimatic

Table 2
Study variables used for CSAF land suitability assessment.

S/N	Variables	Data Types	Resolution
1	Study area boundaries	Vector data: used to extract the study area boundaries	1:200,000
2	Rainfall	Raster data: used to extract the mean annual rainfall of the study area	180×180m
3	Temperature	Raster data: used to extract the mean annual temperature of the meteorological stations in the study area	180×180m
4	Elevation	Raster data: used to extract the altitude of the study area	30 x 30m
	Slope	Raster data: used to extract the slope of the study area	30×30m
5	LU/LC	Raster data: used to extract the LU/LC of the study area	180×180m
6	Soil type	Raster data: used to extract soil types of the study area	180×180m
7	Euclidian Distance to roads (ED)	Vector data: used to extrapolate distance from roads of CSAF in the study area	180×180m
8	Euclidian Distance to trade (ED)	Vector data: used to extrapolate distance from trade of CSAF in the study area	110×110m
9	Landslide risk	Vector data: used to extract erosion hazards of the study area	180×180m

zones.

Both study areas (Bugesera and Rulindo) were the basis for the extraction of these files before running spatial analysis and building up the models. We used the ArcGIS 10.8 software from Esri (Redlands, California, USA) to fulfill this process. The data used in the analysis and mapping for CSAF land suitability included the elevation, slope, soil type, rainfall, temperature, LU/LC, and landslide risks. Roads and trade centers were used as shapefiles and were rated based on Euclidean distances (ED) (Figs. 4 & 5).

2.6. Generating standardized criteria maps

The nine variables selected for use in this study were in different units of measurement. So, before adopting the weighted overlay method, those variables were converted into the same units of measurement for coherence and hence required to be standardized values. The data standardization techniques entail re-scale feature values to uniform units (Effat and Hassan, 2013), in which data are transformed to a more consistent scale (the resulting scores lose their dimension along with their units of measurement).

Analysis of these geographic data also involved the conversion of vector layers to raster layers. All raster layers were reclassified and were used for the input data to the weighted overlay method used to create the suitability maps for CSAF in the study area. The reclassify tool in the spatial analyst toolbox of Arc-GIS software standardizes the values of all selected variables for comparative analysis (Pramanik, 2016).

Modern farming which involves the latest technical practices, inter alia CSAF, requires assessment of inherent biophysical and climatic features, with access to roads and trade facilities. The last two parameters facilitate access to inputs and raw products to and from the farms. In the identification of suitable sites, all these parameters were considered to examine the potential extension zones for CSAF.

2.7. Determination of weight for each variable

The AHP was used to assign the weight of importance to the selected parameters based on pairwise comparisons according to their relative significance. Spatial analysis in agriculture uses AHP-based MCDM (Yanos and Udan, 2022). AHP was first coined by Saaty (1980). It is an

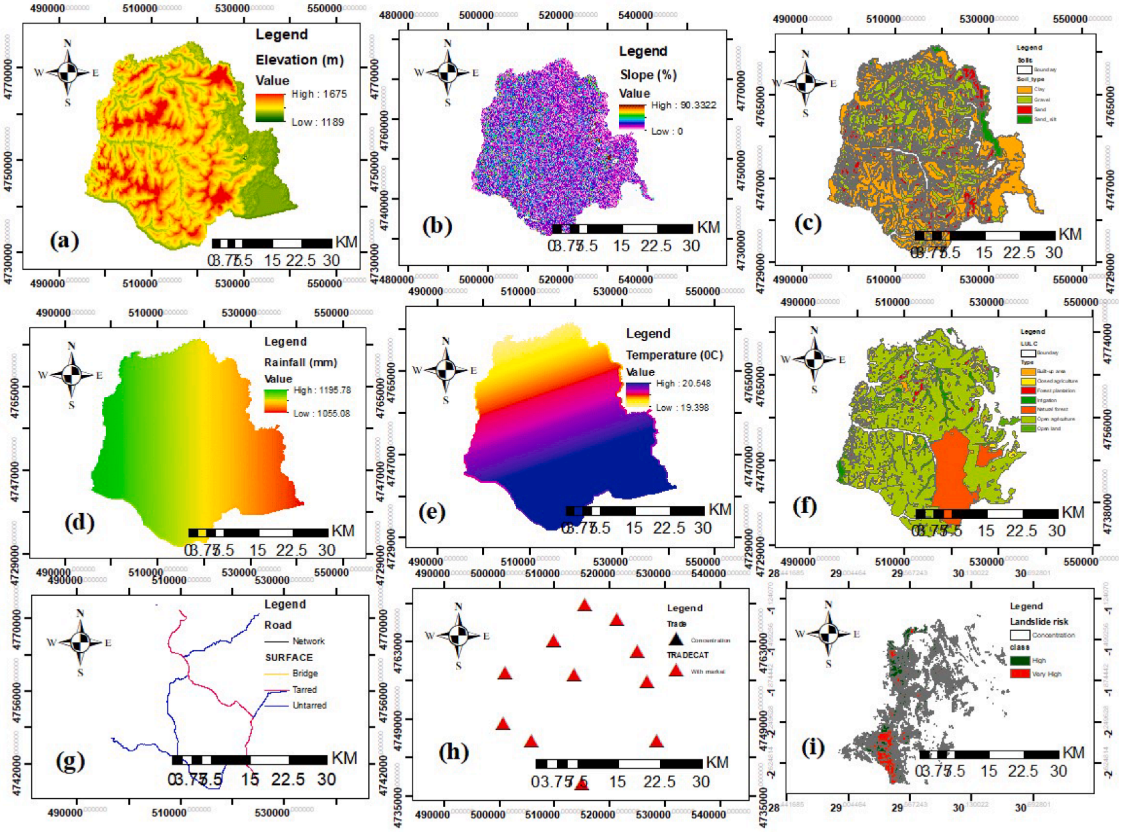

Fig. 4. Suitability layers for CSAF in Bugesera: (a) Elevation (b) Slope (c) Soil (d) Rainfall (e) Temperature (f) LU/LC (g) Road (h) Trade center (i) Landslide risk.

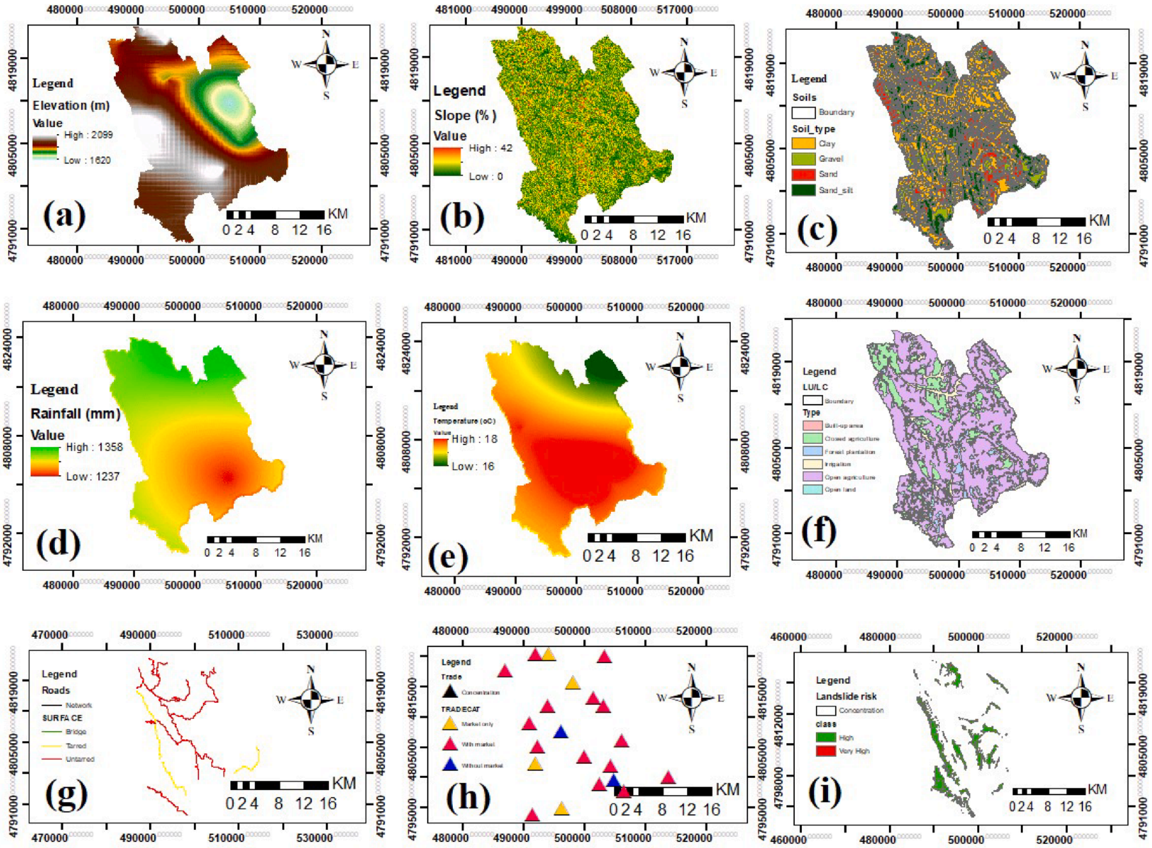

Fig. 5. Suitability layers for CSAF in Rulindo: (a) Elevation (b) Slope (c) Soil (d) Rainfall (e) Temperature (f) LU/LC (g) Road (h) Trade center (i) Landslide risk.

intuitive method for tackling MCDM problems and articulating and analyzing conclusions (Saaty, 1980). The approach was introduced to establish a hierarchical model for solving complex problems of land use with the options (Roig-Tierno et al., 2013).

AHP is applied to a set of variables to build a hierarchical structure by assigning weight to each variable in the decision-making process. The assigned weight value denotes the relative significance of variables and they are deliberately assigned (Pramanik, 2016). In this study, we applied the AHP by constructing a two-by-two comparison matrix of all the study variables. Thus, in the comparison matrix, a value of 1 was attributed to variables with equal importance, while a value of 9 was attributed to those that were of extreme importance (Table 3).

The pairwise comparison matrix of this study is presented in Table 4. The process consisted of filling variables into a comparison matrix, values were also filled from 1 to 9 where fractions from 1/2 to 1/9 depict the importance of one factor over another in the pair. Additionally, the 9th-order matrix consistency was estimated. This method uses subjectivity in comparisons (Chuma et al., 2021), and the tolerated AHP inconsistency given the volume of redundancy occurring in the process. During the process, the responses to the comparisons were re-examined until this consistency index (CI) reached the required threshold level. After concluding this step, the next phase involved spatial analyses with ArcGIS 10.8 (Fig. 6).

As illustrated in Table 4, the weight for priorities and eigenvector values were computed from a pairwise comparison matrix based on the following equation (Hamere and Teshome, 2018):

$$Eigen\ vector = A_{ij} = \frac{\sum_{i=1}^{n}\left(w1/w1 \times w1/w2\ldots \times w1/wn\right)^{1/n}}{\sum\left[\sum_{i=1}^{n}\left(w1/w1 \times w1/w2\ldots \times w1/wn\right)^{1/n}\right]} \quad \text{(Eq. 1)}$$

Where, W_i is the sum of rows for pairwise comparison, and n is the size of the matrix.

Table 3
Suggested rating scales for AHP in a pairwise comparison matrix.

Scale of judgment	Definition	Explanation
1	Equal importance	Two criteria contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one criterion over another
5	Essential or strong importance	Experience and judgment strongly favor one criterion over another
7	Very strong or demonstrated importance	Criterion is strongly favored and its dominance demonstrated in practice
9	Absolute importance	The evidence favoring one criterion over another is of the highest possible order of affirmation
2–4–6–8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals	If criterion *i* has one of the above numbers assigned to it when compared with criterion *j*, then *j* has the reciprocal value when compared with *i*	
Rationals	Ratios arising from the scale	If consistency were to be forced by obtaining *n* numerical values to span the matrix

Source: Adapted from Saaty (1987).

The calculation of the consistency ratio (CR) was done to check the consistency of comparisons in the matrix. As a rule of thumb, the sum of weights for all variables involved in the process should be equal to 1. Logically, the consistency ratio (CR) ranges from 0 to 1. Accordingly, a CR approaching 1 indicates the probability that rating the matrix was done randomly. A computed consistency ratio (CR) of 0.1 or less constitutes a reasonable level of consistency. Results in this study exhibited

Table 4
Pairwise comparison matrix matching.

Variables	Pairwise comparison matrix								
	Elevation	Slope	Soil	Rainfall	Temp	Land	Landslide risk	ED to road (km)	ED to trade (km)
Elevation	1	2	3	7	5	7	4	3	3
Slope	0.5	1	2	2	2	3	6	2	8
Soil	0.333	0.5	1	2	2	5	3	7	5
Rainfall	0.142	0.5	0.5	1	2	5	3	2	4
Temp	0.2	0.5	0.5	0.5	1	3	3	5	2
Land	0.142	0.333	0.2	0.2	0.333	1	3	4	2
Landslide risk	0.25	0.166	0.333	0.333	0.333	0.333	1	3	3
ED to road (km)	0.333	0.5	0.142	0.5	0.5	0.25	0.333	1	3
ED to trade (km)	0.333	0.125	0.2	0.25	0.5	0.5	0.333	0.333	1

ED = Euclidean distance.

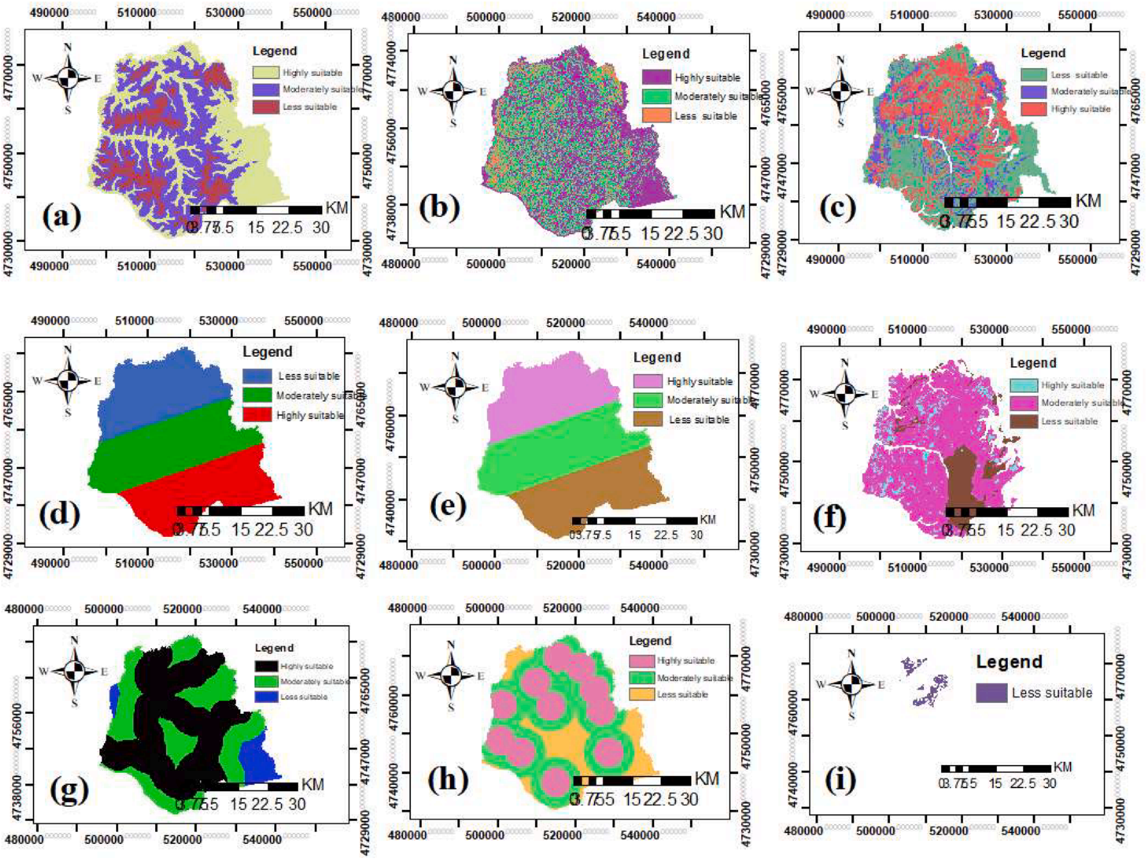

Fig. 6. GIS-based standardized thematic maps for CSAF (Bugesera): (a) Elevation suitability map (b) Slope suitability map (c) Soil suitability map (d) Rainfall suitability map (e) Temperature suitability map (f) LU/LC suitability map (g) ED to roads suitability map (h) ED to trade centers suitability map (i) Landslide risk suitability map.

a CR of 0.053843448 from the paired comparison matrix between 9 factors, which indicates logical judgment.

The consistency index (CI) was computed from the equation below (Hamere and Teshome, 2018):

$$CI = \frac{\lambda max - n}{n - 1} \qquad \text{(Eq. 2)}$$

Where, λmax is the largest eigenvalue of the pairwise comparison matrix and n is the number of classes.

Then, CR is given by the equation below (Saaty, 1980):

$$CR = \frac{CI}{RI} \qquad \text{(Eq. 3)}$$

Where, RI is the ratio $\frac{index}{average}$ value of CI for random matrices using the Saaty (1980) scale.

Further, the computed weight values are converted into relative values (percentages) for weighted overlay analysis in GIS (Tables 4 & 5).

2.8. *Suitability model building for CSAF extension in study areas*

The land suitability model for CSAF in study areas was generated using a weighted overlay (WO) approach. The integration of WO with the AHP provides an accurate outcome for the site suitability assessment for technology implementation in modern farming. All created thematic layers were combined in the GIS environment to apply the WO techniques. The nine operated raster layers were overlaid by bringing their cell values to the same scale, assigning a weight value to the individual variable, and integrating the weight cell values (Eq. (4)).

Table 5
Normalized matrix with normalized weight for each thematic layer.

Variables	Normalized pairwise comparison matrix										
	Elevation	Slope	Soil	Rainfall	Temp	Land	Landslide risk	ED to road (km)	ED to trade (km)	Priority vector	Weight (%)
Elevation	1	2	3	7	5	7	4	3	3	0.297904	30
Slope	0.5	1	2	2	2	3	6	2	8	0.187239	19
Soil	0.333	0.5	1	2	2	5	3	7	5	0.164528	16
Rainfall	0.142	0.5	0.5	1	2	5	3	2	4	0.096358	10
Temp	0.2	0.5	0.5	0.5	1	3	3	5	2	0.085377	9
Land	0.142	0.333	0.2	0.2	0.333	1	3	4	2	0.051824	5
Landslide risk	0.25	0.166	0.333	0.333	0.333	0.333	1	3	3	0.045783	4
ED to road (km)	0.333	0.5	0.142	0.5	0.5	0.25	0.333	1	3	0.047945	5
ED to trade (km)	0.333	0.125	0.2	0.25	0.5	0.5	0.333	0.333	1	0.023043	2

Principal Eigen Value = 9.624582 Consistency Index (CI) = 0.078073 Consistency Ratio (CR) = 0.053843448 ≈ 5 %.

$$S = \sum_{i=0}^{n} (W_i X_i) \qquad \text{(Eq. 4)}$$

where S is the total land suitability score for CSAF, W_i is the weight of factor i, and $X_i$is the variable score of factor i, and n denotes the total number of land capability (Cengiz and Akbulak, 2009).

Analysis involving various steps was undertaken starting with raster images' reclassification followed by the determination of the "Euclidean distance" (in km) for roads and trade centers. Slopes were generated from DEM in ArcGIS. Thereafter, the rasters obtained were reclassified into different classes according to their constraints to the adaptability in CSAF. Finally, the classes obtained were again reclassified according to a three-level scale which was similar to the "Likert-scale" (Lewis and Erdinç, 2017). Obtained classes were termed as follows: "highly suitable, moderately suitable, and less suitable". After recalculation of all the variables, the WO tool was used to produce the suitability classes for CSAF. For each variable, a weight factor given in Table 1 was used at the end when producing the final result. Finally, the resulting raster was then reclassified into three suitability classes as illustrated in Table 7.

2.9. *Matching the CSAF suitability model with ground-truthing*

A field visit was done in the study areas to verify the extent of CSAF for the validation of the final CSAF suitability maps for the two zones. The final suitability maps were validated through field visits to collect information on actual CSAF practices in the two sites. Given the vastness and complex relief of the study area, it was not practicable to validate the whole area through a probability (random) sampling approach. We then selected three sites, one from the eastern lowlands (Nyamata in Bugesera) and two from the central highlands (Rukozo and Bushoki in Rulindo), and randomly selected some locations of existing CSAF and recorded the geo-coordinates from those locations. The ground-based CSAF records were processed in GIS and overlaid on the CSAF suitability maps. The accuracy of the final suitability maps was determined by comparing the model output with the corresponding actual CSAF information collected from the field.

Also, we cross-checked the literature to verify suggested suitability classes for CSAF by comparing the relevant information on CSAF.

3. Results

3.1. *Suitability classes of land for CSAF extension in study areas*

The computation of CI was done as follows: $CI = (\lambda_{max} - n)/(n - 1)$ with λ_{max}: the maximum eigenvalue of the matrix, and n: the number of variables (here n was 9). *CI* has been compared to a random matrix *RI* (Random Inconsistency Index, *RI* for $n = 9$ was 1.45) (Table 6). The derived $\frac{CI}{RI}$ ratio, called the Consistency Ratio (CR), was also obtained (Table 5). To validate the matrix and the weights obtained for each factor, a threshold as suggested by Saaty (1980) was adopted, that is to say, the *CR* ratio should be less or equal to 0.10. For our case, *CI* was estimated at 0.078073 and a *CR* of 0.053843448 (Table 5) whose value is < 0.10 consistency ratio standard recommended by Saaty (1980). As such, both good consistency and coherence complied with the ratio standard for the selected variables.

Both biophysical and socioeconomic factors inherent to CSAF practices were classified (Table 5) using biophysical and economic constraints and weights were attributed based on Saaty (1980)'s AHP in Tables 4 & 6. The results computed in Tables 4 and 5 were used as inputs in building suitability maps for CSAF.

Table 7 shows the weight attributed to the variables used in the study. The elevation variable was given the highest weight with a 30 % level of importance, while ED to trade was assigned the least level of importance with 2 %. The variables were ranked based on the suitable and favorable conditions for adaptability and CSAF scaling up. The results computed in Table 7 were then utilized in the GIS model environment to classify variables and for the final WO.

3.2. *Standardized suitability maps of thematic layers for CSAF in Bugesera and Rulindo*

Features inherent to the growth of various CSAF trees (soil type, elevation, slope, rainfall, and temperature) were brought for GIS analysis and weight was ascribed to each thematic layer based on Table 5 which was generated in a pairwise comparisons process, a widely accepted statistical tool in GIS mapping. Table 8 presents classes for each variable selected for the CSAF land suitability analysis for Bugesera and Rulindo. The area in hectares and the relative values (percentages) of classes were determined based on the total surface of the study area.

For the Bugesera physiographic zone, we found that for elevation, almost 40 % (50,033.25 ha) of Bugesera was classified as highly suitable for CSAF (<1000 m), and 42.8 % (52,435.89 ha) was moderately suitable (1000–1500 m). For the slope, only 8.46 % (10,314.81 ha) of the area was less suitable (>25 %) for the CSAF upscale. The dominant soil types were clay classified as moderately suitable (53.27 %) and sand as highly suitable (31.98 %). These medium-textured soils (sand and clay) are often considered ideal for agriculture as they are easily cultivated by farmers and can be highly productive for crop growth (Parikh and

Table 6
Table of random Index (RI) values as per Saaty (1980).

n	1	2	3	4	5	6	7	8	9[a]	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.58

[a] The RI value for 9 criteria is 1.45.

Table 7
Weight matrix of variables for suitability mapping in study areas.

Variables	Weight (%)	Value/ Description	Ranks	Suitability
Elevation	30	< 1000m	3	Highly suitable
		1000–1500m	2	Moderately suitable
		>1500m	1	Less suitable
Slope	19	<10 %	3	Highly suitable
		10–25 %	2	Moderately suitable
		>25 %	1	Less suitable
Soil	16	Gravel	1	Less suitable
		Clay	2	Moderately suitable
		Sand	3	Highly suitable
Rainfall	10	< 1000mm	1	Less suitable
		1000–1100mm	2	Moderately suitable
		>1100mm	3	Highly suitable
Temp	9	<15 °C	3	Highly suitable
		15–20 °C	2	Moderately suitable
		>20 °C	1	Less suitable
Land	5	Settlement	3	Highly suitable
		Agriculture	2	Moderately suitable
		Forest	1	Less suitable
Landslide risk	4	Grid code: 4	3	Highly suitable
		Grid code: 5	2	Moderately suitable
ED to road (km)	5	<1km	3	Highly suitable
		1–5km	2	Moderately suitable
		>5km	1	Less suitable
ED to trade (km)	2	<1km	3	Highly suitable
		1–5km	2	Moderately suitable
		>5km	1	Less suitable

James, 2012). Gravel was classified as less suitable because soils with high gravel content work as a barrier to plant growth; plants cannot grow in these types of soils because they can't obtain sufficient nutrients from gravel soils; these soils lack fertilizer; the gravel attending in the soil pierces the roots generating damage to plants. Subsequently, it is clear that CSAF is not a suitable option for these soils. Slightly above half (55.49 %) of the area was classified as close to the roads (< 1 km) and was considered highly suitable for CSAF. Regarding the distance from trading centers, 36.94 % (47,671.58 ha) were classified as highly suitable because they are located at <1 km. The same observation and trend could be observed in terms of distance from settlements, health facilities, schools, and water bodies. As far as rainfall and temperature were concerned, 31.18 % (40,227.23 ha) and 31.19 % (40,040.49 ha) were presented as highly suitable land, respectively. The Bugesera suitability maps of these nine classification variables are presented in Fig. 6.

Regarding the Rulindo physiographic zone (Table 8), results showed that for elevation, 17.55 % (623.52km2) area lies on lower elevation which is highly suitable for CSAF. Regarding the slope, slightly above half (52.45 %) of the land area is highly suitable for CSAF on gentle slopes (<10 %). The dominant soil types were clay classified as moderately suitable (49.07 %) and sand being highly suitable (25.57 %). More than half (61.47 %) of the area was classified as close to the roads (< 1 km) and was considered highly suitable for CSAF. Regarding the distance from trading centers, 32.04 % (15,307.71 ha) was classified as highly suitable because they are located at <1 km. For rainfall and temperature, 32.91 % (42,576.19 ha) and 12.4 % (16,046.34) were presented as highly suitable land, respectively. It is important to note that in the highlands of Rwanda, the local people are used to building terraces on hillslopes and performing rain-fed farming practices on land that seems unfit for agricultural activities.

High elevation (>1500 m), and steep slope (>25 %) with higher intensity of erosion were common characteristics, resulting in a lower rate of suitable CSAF in Rulindo. Fig. 7 presents classes for each variable used for the CSAF land suitability analysis in Rulindo.

Table 8
Variables used in suitability analysis for CSAF in Bugesera and Rulindo.

Variables	Suitability	Suitability range	Bugesera Area (ha)	Rulindo Area (ha)
Elevation	Highly suitable	< 1000m	50,033.25 (40.91 %)	623.52 (17.55 %)
	Moderately suitable	1000–1500m	52,435.89 (42.87 %)	1674.27 (47.11 %)
	Less suitable	>1500m	19,839.96 (16.22 %)	1256.13 (35.34 %)
Slope	Highly suitable	<10 %	63,068.94 (51.76 %)	27,994.32 (52.45 %)
	Moderately suitable	10–25 %	48,469.77 (39.78 %)	19,073.79 (35.73 %)
	Less suitable	>25 %	10,314.81 (8.46 %)	6307.56 (11.82 %)
Soil type	Less suitable	Gravel	64,424.16 (53.27 %)	62,496.36 (49.07 %)
	Moderately Suitable	Clay	17,842.68 (14.75 %)	32,299.56 (25.36 %)
	Highly suitable	Sand	38,672.64 (31.98 %)	32,578.20 (25.57 %)
Rainfall	Less suitable	< 1000mm	40,227.23 (31.18 %)	42,576.19 (32.91 %)
	Moderately suitable	1000–1100mm	47,464.14 (36.78 %)	61,593.96 (47.61 %)
	Highly suitable	>1100mm	41,341.11 (32.04 %)	25,196.48 (19.48 %)
Temperature	Highly suitable	<15 °C	40,040.49 (31.19 %)	16,046.34 (12.4 %)
	Moderately suitable	15–20 °C	47,467.41 (36.97 %)	51,379.08 (39.72 %)
	Less suitable	>20 °C	40,882.45 (31.84 %)	61,941.22 (47.88 %)
LU/LC	Highly suitable	Settlement	8041.68 (7.61 %)	18,338.40 (14.39 %)
	Moderately suitable	Agriculture	79,554.96 (75.25 %)	20,324.52 (15.96 %)
	Less suitable	Forest	18,124.56 (17.14 %)	88,714.44 (69.65 %)
ED to roads	Highly suitable	<1km	71,595.89 (55.49 %)	79,517.50 (61.47 %)
	Moderately suitable	1–5 km	47,464.14 (36.79 %)	38,346.75 (29.64 %)
	Less suitable	>5km	9959.34 (7.72 %)	11,502.39 (8.89 %)
ED to trade	Highly suitable	<1km	47,671.58 (36.94 %)	15,307.71 (32.04 %)
	Moderately suitable	1–5 km	55,086.46 (42.68 %)	19,579.01 (40.98 %)
	Less suitable	>5km	26,301.77 (20.38 %)	12,893.76 (26.98 %)
Landslide	Highly suitable	High	3463.56 (100 %)	40,989.24 (32.04 %)
	Moderately suitable			52,426.44 (40.98 %)
	Less suitable			34,525.44 (26.98 %)

The combination of the nine variables to determine land suitability for CSAF in Bugesera and Rulindo is presented in Fig. 8. After ascribing weights to each variable (weighting the input layers) and its reclassification into three classes by overlaying them using the WO tool in ArcGIS 10.8, different classes were discerned.

3.3. *Generation of suitability map for CSAF in Bugesera and Rulindo*

For the Bugesera physiographic zone, the statistics in Table 9 show that 1.60 % (1662.82 ha) of Bugesera is highly suitable and 86.62 % (90,123.78 ha) is moderately suitable for CSAF. While 11.78 %

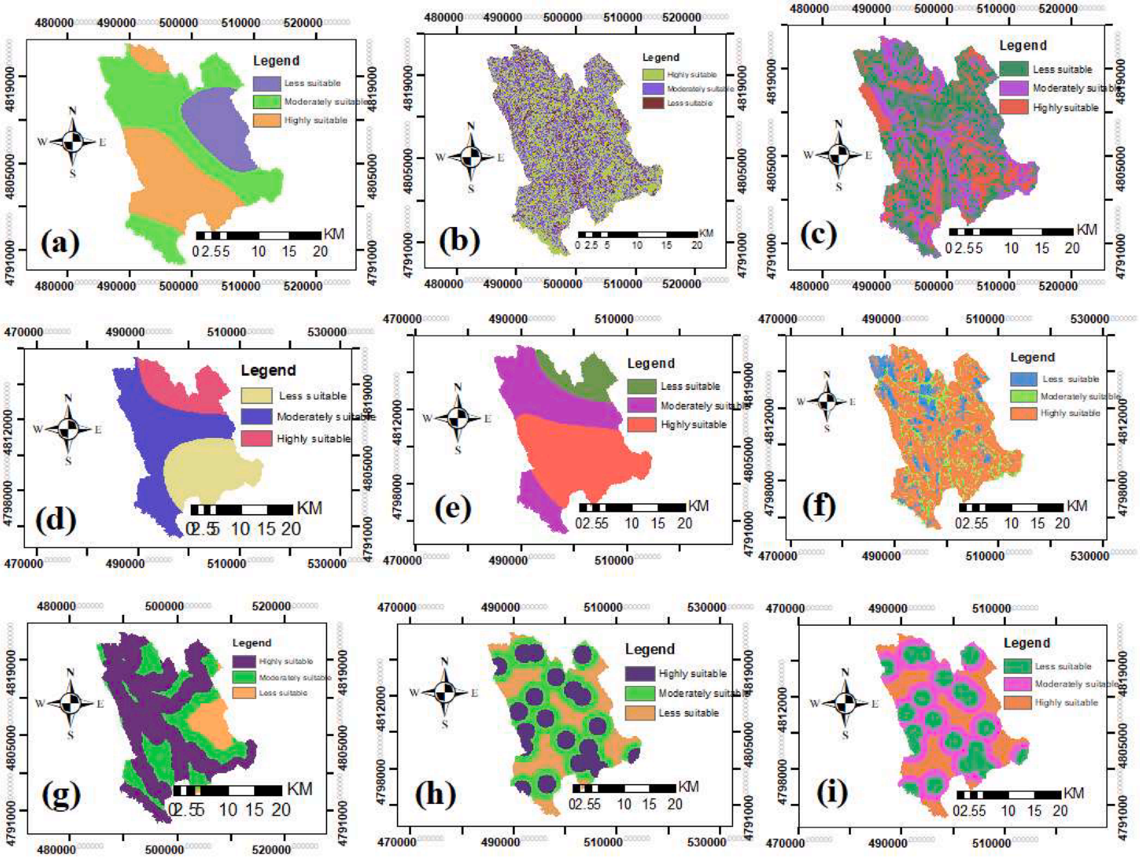

Fig. 7. GIS-based standardized thematic maps for CSAF (Rulindo): (a) Elevation suitability map (b) Slope suitability map (c) Soil suitability map (d) Rainfall suitability map (e) Temperature suitability map (f) LU/LC suitability map (g) ED to roads suitability map (h) ED to trade centers suitability map (i) Landslide risk suitability map.

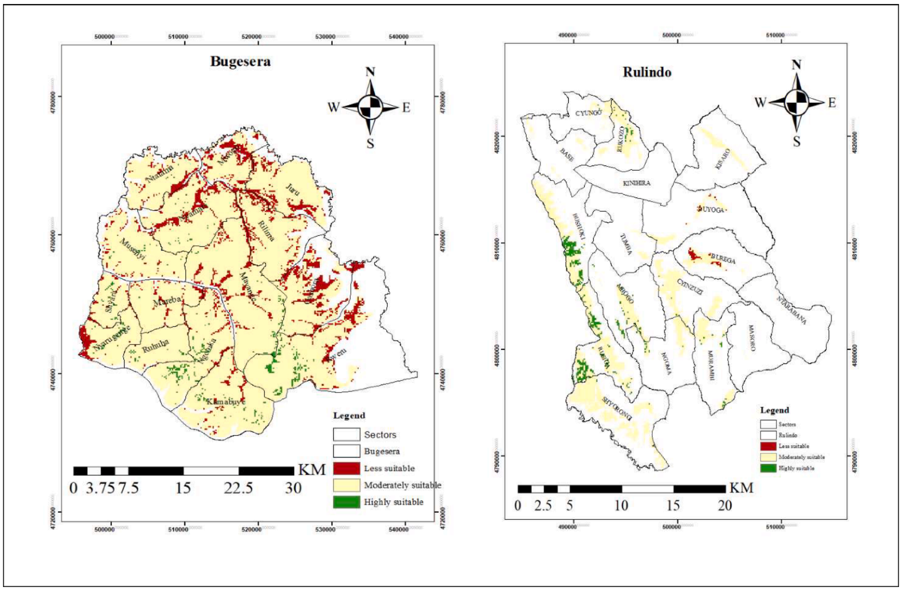

Fig. 8. Bugesera and Rulindo composite CSAF suitability map.

(12,262.50 ha) represent moderately suitable land for CSAF. Fig. 8 shows that the agricultural zones that are moderately suitable and highly suitable for CSAF cover almost all sectors of Bugesera (88.22 %), a rural area largely agrarian. The remaining area that is less suitable for CSAF (11.78 %) is categorized as soils hit by prolonged drought, water bodies, marshlands, forests, and bushlands. Land that is less suitable for CSAF in Bugesera is equally scattered across almost all sectors mainly in Juru, Rilima, Gashora, and Rweru alongside the complex of lakes and marshes of Bugesera (Rweru, Mugesera, and Sake) in eastern, Nyarugenge, Shyara and Musenyi alongside Akanyaru river in western,

Table 9
Areal distribution of land suitability analysis results for CSAF in Bugesera and Rulindo.

	Bugesera	Rulindo
Suitability	Area (ha)	Area (ha)
Less suitable	12,262.50(11.78 %)	102.24(1.39 %)
Moderately suitable	90,123.78(86.62 %)	6514.56(88.92 %)
Highly Suitable	1662.82(1.60 %)	709.92(9.69 %)

Ntarama and Mwogo alongside Nyabarongo river in northern, Nyamata, Mayange and Ngeruka in Central and Kamabuye in southern. For increased agricultural production in Bugesera, the ongoing and future CSAF schemes can be diverted to moderately suitable and highly suitable areas identified in this study mainly dominated by arable land.

Regarding the Rulindo physiographic zone (Table 9), the statistics show that 9.69 % (709.92 ha) of Rulindo is highly suitable and 88.92 % (6514.56 ha) is moderately suitable for CSAF. While 1.39 % (102.24 ha) represents land that is less suitable for CSAF. Fig. 8 shows that the areas identified as moderately suitable and highly suitable for CSAF cover the major part of Rulindo (98.61 %) which is rural and largely agrarian. The remaining area that is less suitable for CSAF (1.39 %) is more categorized as marshlands (Kinihira, Tumba zones), water bodies (Muyanza artificial lake in Buyoga), deposits of clay and peat, and minerals and quarries concessions present in zones of Burega, Murambi, Masoro, Cyinzuzi, and Ntarabana. The sectors of Rusiga, Bushoki, and Mbogo in the western part, Rukozo, and Cyungo in the northern, Murambi and Ngoma in the southern and Cyinzuzi in the center has the maximum area of arable land either moderately suitable or highly suitable for CSAF. In short, zones of high suitability and moderate suitability level should therefore be privileged in expanding the CSAF practices in Rulindo.

3.4. Cross-site comparative analysis

This study also showed that the available means suitable land for CSAF is 34,683.03 ha in Bugesera (34,683.03 ± 48,304.71) and 2442.24 ha in Rulindo (2442.24 ± 3539.79). The SD is larger in both sites and amply suggests that this was due to larger variation in the data with a range of 88,460.95 ha (1662.82 — 90,123.78 ha) in Bugesera and 6412.32 ha (102.24 — 6514.56 ha) in Rulindo. Moreover, land suitability scores for CSAF largely varied across sites ($F = 1.33$, $p = 0.31$).

As expected, the proportions of suitable areas for CSAF varied with sites in the study areas of Bugesera and Rulindo (Fig. 9). Highly suitable zones were observed in Bugesera for 1662.82 ha (1.6 %) against 709.92 ha (9.69 %) in Rulindo, moderately suitable areas observed in Bugesera were 90,123.78 ha (86.62 %) against 6514.56 ha (88.92 %) in Rulindo while less suitable areas observed in Bugesera were 12,262.50 ha (11.78 %) against 102.24 ha (1.39 %) in Rulindo.

3.5. Matching the CSAF suitability model with ground-truthing in Bugesera and Rulindo

We conducted a field visit and collected GPS-based ground coordinates of 11 random locations of actual CSAF from the two selected contrasting agroecological zones ((Bugesera (6 points) and Rulindo (5 points)) (Fig. 10). The CSAF points from the GPS locations were matched with corresponding locations in the CSAF suitability maps. Out of the 11 ground-based locations, 10 points (nearly 91 %) supported the model output, and the remaining locations were found to be located under the less suitable class. These locations that are less suitable, 1 point (about 9 %), were found in the Bushoki sector (Rulindo) at 2108.647 m of altitude classified as a “less suitable” area since highlands are appropriate to moderate and dense forests or upland pastures. The result of the class-wise comparison of ground verification points with the model-derived suitability classes is presented in Table 10.

4. Discussion

Climate-smart agroforestry (CSAF) denotes a practiced farming system of combining trees with crops or animals (AF) evolved in practices to enhance productivity and feed the food-insecure people while coping with the adverse effects of climate change. Some of the CSAF practices worldwide are alley cropping, home gardens, silvopasture, taungya systems, and shelterbelts and windbreaks (Gold et al., 2000).

This study indicates that in Bugesera and Rulindo, highly suitable areas for CSAF are covered by 1662.82 ha and 709.92 ha, respectively. This study also revealed that about 90,123.78 ha and 6514.56 ha in Bugesera and Rulindo, respectively, are moderately suitable for CSAF, while about 12,262.50 ha and 102.24 ha are less suitable for CSAF purposes in Bugesera and Rulindo, respectively. Similar studies on CSAF evaluation carried out around the globe also realized the high significance of climatic factors and local environmental conditions that contribute to the successful development of CSAF systems (Szott et al., 1991).

Verification in the field also revealed that locations in high elevations are not suitable for CSAF purposes (about 9 %) in the Bushoki sector (Rulindo) at 2108.647 m of altitude. Akinci et al. (2013) also computed and found a lower rate of 0.4 % area for suitable agriculture in a study of agricultural land suitability evaluation for the hilly areas of Ispir, Erzurum (Turkey). Similarly, these results are confirmed by Girmay et al. (2018) who reported that the limiting factors for CSAF purposes include topography (slope) during their assessment of land capability and suitability for wheat crop farming in Ethiopia. This study signifies that steep slopes in Rulindo not only indicate the common agrarian landscapes but restrict the potential agricultural production in the study region.

This study established that bare soils on steep slopes without CSAF covers have risks of natural disasters such as soil erosion, and landslides

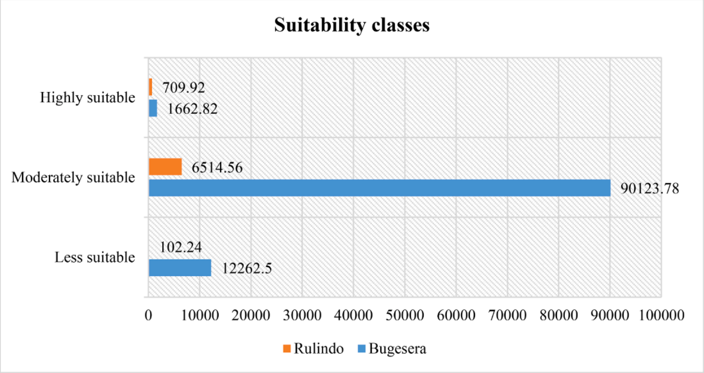

Fig. 9. Variation of suitability classes for CSAF (value above each bar denotes the area (ha)).

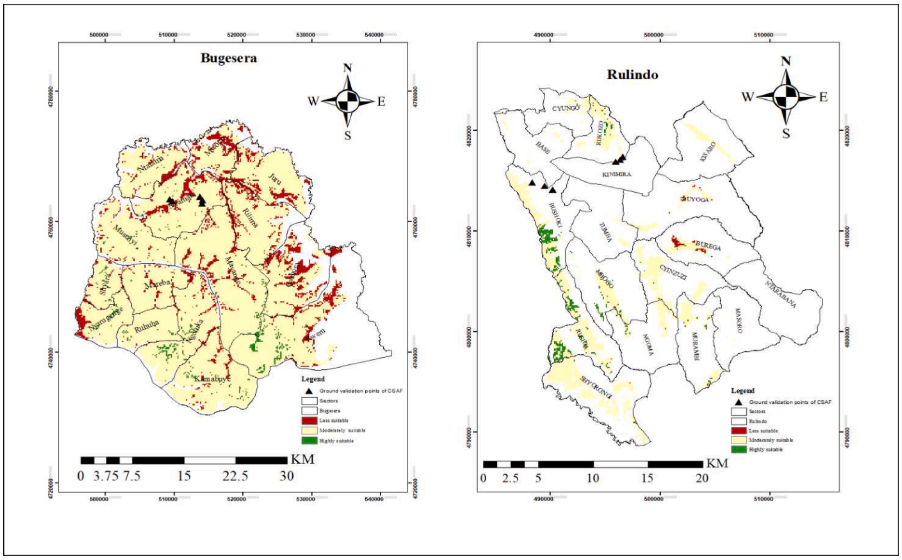

Fig. 10. GPS-based ground validation points of CSAF in Bugesera and Rulindo.

Table 10
Matching field results with model-derived classes for CSAF.

On-farm arrangement practices	Model-derived CSAF suitability class				
	Highly suitable	Moderately suitable	Less suitable	Total	Matching (%)
Home-garden	3	0	0	3	100
Alley cropping	2	3	1	6	83
Plantation-crop combination	2	0	0	2	100

occasioned by heavy rains that lead sometimes to loss of lives. Comparable results in South Kivu (DRC) support these findings, that the establishment of the CSAF approach was uniquely intended and linked to erosion management and control, which was, one of (if not the major) the land degradation factors in the region (Chuma et al., 2021). Additionally, the finding corroborates that of Chuma et al. (2021) who found that formerly, in South Kivu, the CSAF was used for riverbank stabilization, road and roadside stabilization, gully rehabilitation and erosion control, afforestation and commercial tree plantations, and integration of trees into pastures.

Healthy soils (such as adequate pH) and topographic factors (low elevation and gentle slope) along with climatic parameters such as optimum rainfall and temperature conditions are vital for tree species distribution, growth, and adaptation (FAO, 2008) which highly influence and determine their site suitability and hence productivity and high yields. Evaluation carried out on CSAF in other parts of the world also realized the high significance of soils, topographic, and climatic factors, and local environmental conditions that contribute to crop-tree integrated farming systems.

In the recent past, the government of Rwanda ventured into the construction of the Muyanza irrigation dam in Rulindo which is expected to contribute to transforming agricultural production — historically prone to climate change, and food shortage. These findings corroborate Bhutia (2014) who found that the construction of large dams and reservoirs played a significant role in Darjeeling's investment budget while solving environmental problems in Darjeeling district and its immediate environment. It is also common that large dams and reservoirs can transform the river systems they are built on and their surrounding environment (Bhutia, 2014). The project provided some environmental services such as soil water erosion control, soil fertility improvement, water conservation, microclimate improvement, and creation that could improve agricultural productivity and landscape resilience (Chuma et al., 2021).

Similarly, this study revealed that the areas identified as moderately suitable and highly suitable for CSAF cover the major parts of Rulindo (98.61 %) and Bugesera (88.22 %) which are both rural and largely agrarian. Moreover, results show that the area of cropland, forest, and built-up/settlement in Bugesera and Rulindo accounted for 75.25 %, 17.14 %, 7.61 %, and 15.96 %, 69.65 %, 14.39 %, respectively, as the main LULC types. Li et al. (2021) found nearly similar results that forest, grassland, and cropland were the main LULC types in their analysis of how Rwandan LULC changes under high population pressure and changing climate. They noted that a massive conversion of forests into cropland (agriculture) was attributed to the lack of sustainable and effective land management measures.

Land suitability mapping would allow the identification of sites with high potential for CSAF. Depending on the scale of analysis, suitability assessments using suitability maps can serve in the design, adoption, promotion, and planning of farming systems integrating trees with crops (Bentrup and Leininger, 2002). Suitability assessment using suitability maps can disclose a range of alternative products that can be grown in a region, providing a case for cost-share and other assistance programs designed to encourage crop diversification and integration (Bentrup and Leininger, 2002). The land suitability assessment is a powerful approach that can be used to identify the range of specialty products induced by CSAF for any given tract of land, giving landowners the power to integrate the best tree species into farming operations. Once suitability models are set up, it follows that the industry can provide support for CSAF expansion to other zones by demonstrating how CSAF helps agricultural producers with problems, for example, in highly erodible lands.

5. Conclusion

Climate-smart agroforestry (CSAF) constitutes a novice in modern farming, hence there exists limited literature on land evaluation for various CSAF practices using remote sensing (RS) and geographic information systems (GIS). To scale up this farming practice, land must be evaluated to predict its availability and suitability. The land suitability classification entails the appraisal and grouping of a particular geographical area based on its suitability for a specified purpose. Land appropriateness is the degree to which a piece of land is suitable for a given and particular use. Using the geographic information system (GIS) and analytic hierarchy approach (AHP), researchers evaluated CSAF farming in the Bugesera and Rulindo zones of Rwanda. An integrated application of GIS and AHP-based land suitability analysis for CSAF elucidated highly and less adaptative sites. Weights were estimated on selected variables in order to account for AHP's influence on land suitability classification. Results identified three CSAF suitability zones, ranging from 1662.82 ha (1.60 %) as highly suitable and 90,123.78 ha (86.62 %) as moderately suitable to 12,262.50 ha (11.78 %) less suitable zones in Bugesera. In Rulindo, suitability zones range from 709.92 ha (9.69 %) as highly suitable and 6514.56 ha (88.92 %) as moderately suitable to 102.24 ha (1.39 %) less suitable land for CSAF. This study integrates GIS with AHP to plan CSAF farming and scaling up. In sites such as Bugesera and Rulindo where investigations on CSAF are scanty, these results reveal the extent of CSAF farming in the targeted areas. They can provide direction for future land use modifications, better land stewardship, and cost-effective solutions in study areas, and other agroclimatic zones. Moreover, this study will pave the way for further studies on the potential CSAF and possibly required interventions for the assessed areas.

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CRediT authorship contribution statement

Donatien Ntawuruhunga: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Software, Writing – review & editing, Visualization. **Edwin Estomii Ngowi:** Writing – original draft, Methodology, Data curation, Validation, Writing – review & editing, Visualization, Supervision. **Halima Omari Mangi:** Writing – original draft, Methodology, Data curation, Validation, Writing – review & editing, Visualization, Supervision. **Raymond John Salanga:** Writing – original draft, Writing – review & editing, Project administration, Supervision. **Kelvin Mashisia Shikuku:** Writing – original draft, Methodology, Data curation, Validation, Writing – review & editing, Visualization, Supervision.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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