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

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Abstract

The unmatched world population growth with production has increased human demand causing starvation consequent to food shortage. Climate-smart agroforestry (CSAF) among other options can enhance productivity, improve income and food security, and stabilize the environment. This study investigates the land suitability for CSAF in the Bugesera and Rulindo regions of Rwanda. After searching the literature and the local expert knowledge and opinions, 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 1,662.82ha (1.60%) as most suitable and 90,123.78ha (86.62%) suitable to 12,262.50ha (11.78%) unsuitable zones in Bugesera. In Rulindo, suitability zones range from 709.92ha (9.69%) as most suitable and 6,514.56ha (88.92%) suitable to 102.24ha (1.39%) unsuitable land for CSAF. Results further showed that the available means suitable land for CSAF are 34,683.03ha in Bugesera (34,683.03 ± 48,304.71) and 2,442.24ha 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) and evidence from literature about existing CSAF mostly supported the generated CSAF suitability maps (nearly 91% of ground-based locations supported the model output). These results reveal the extent of implementation of CSAF practices in the targeted areas. In areas such as Bugesera and Rulindo where investigations on CSAF are scanty, suitability maps in this study would allow identifying sites with high potential for CSAF. The cross-site suitability mapping and analysis for CSAF would provide an opportunity to policy-makers for location-specific land use planning for expanding and implementing CSAF-based models. Those would assist in addressing ecosystem restoration, optimum farm production, increased income, and enhanced food security. 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 trees on farms 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 new practices of combing trees with crops that enhance agricultural productivity but also cope with the adverse effects of the changing climate.

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). According to Octavia et al. (2022), CSAF involves practices aimed not only at land conversion and optimum production, improving and upgrading households' well-being, and improving environmental conditions such as adverse climate, biodiversity enhancement, soil fertility, and water resources while assuring sustainable landscape management. 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).

The domestication of trees into crops dates over several years (Fuller, 2018). Recent insights include the recognition (Fuller, 2018) that based on local knowledge and traditions, farmers have gathered different strategies and practices to minimize crop failures on their farms, sustain yields, ensure food availability (shifting cultivation, fallow, improved seeds, and cultivars), and protect crops against hazards (building terraces, digging anti-erosive ditches and boreholes for irrigating crops). When smart farming practices are effectively and efficiently implemented, agricultural land is more productive and more resilient to climate change (Vilsack, 2021) and other disturbances such as drought, floods, and invasive species. New science and technology development should inform new policies, strategies, and management practices to cope with changing climate (Vilsack, 2021). Given the need to feed the rapid global population growth (Vilsack, 2021), increasing agricultural productivity through sustainable practices is critical. There exist enormous challenges calling for innovative, specialized research in this area in order to address low land productivity and diversify livelihood sources for human betterment (Maleknia et al., 2013). Unfortunately, scientific resources indicate that globally, data on the actual extent of CSAF are scanty (Zomer et al., 2009; Iiyama et al., 2018). Such a situation may hinder the development of CSAF due to the lack of baseline and reliable data necessary to evaluate and scale up CSAF to the next level (Rooney et al., 2004).

Modern well-managed farms with tree-crop farming provide productive, protective, socio-economic, and environmental stability (Simelton and Hoang, 2011). Regarding financial viability, CSAF ensures potential cost-benefit against monocropping practices (Aires, 2008; Do et al., 2020). In their study, Anshiso et al. (2017) proved that beyond profitability, CSAF is less sensitive to changes in output, prices, and discount rates as well as external factors. Mixing crops with trees contributes to soil retention, regeneration, and replenishment and can increase economic returns as well as food self-sufficiency of farmers and practitioners (Kremen et al., 2012). Besides, a reduction in soil erosion exacerbated by landslides on hillslopes and floods in valleys may lead to higher nutrient retention in soil, thus higher crop yields (Hoang et al., 2011). At the landscape scale, emerging scientific evidence supports that CSAF can largely contribute to a range of environmental services (Simelton and Hoang, 2011), inter alia, watershed protection (construction of bench terraces for reducing sedimentation and landslides), maintain larger biodiversity (compared to monocropping systems), carbon sink in soils and trees.

Some researchers stipulate that the low adoption rates of climate-smart technologies constitute a significant hindrance to sustainable agricultural intensification (USAID, 2016). Other scholars found that CSAF can help break the vicious circle of poverty and environmental concerns (Simelton and Hoang, 2011).

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 socio-economic 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 26,336sqkm.

In an effort to feed the fast-growing population and fight hunger, Rwanda has initiated agricultural development programs to boost production and forge raw materials for emerging agroindustry in the country. Despite efforts deployed by the government of Rwanda to cope with the rising food insecurity in the country, limited resources and unreliable agricultural techniques together with recurring food insufficiency, have been alarming largely due to the low level of production in the farming sector that has never matched the growing population (Pender et al., 2006; Himeidan and Kweka, 2012). In its report, the National Institute of Statistics of Rwanda (NISR) (2010) insisted that, 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).

Among the fundamental impediments to agricultural development in Rwanda is the lack of accessibility to data which are not published in accessible portals and independent research on agricultural land potential, diversification of cropping systems, and the public-private partnerships involved in the sector (Kunda et al., 2013). The end result is poor knowledge, uninformed decisions, and unreliable data for agricultural planning and policy formulation deemed to scale up the sector (Kunda et al., 2013). Accordingly, the need to improve agricultural productivity by scaling CSAF practices in farming landscapes across the country is real and urgent. 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 socio-economic data. These features are deemed vital for site characterization and consequently land suitability in site selection for crop production and land conversion for modern, smart farming (FAO, 1995). This study mapped and analyzed the physical features of potentially suitable lands for CSAF in Bugesera and Rulindo regions using available geospatial information (GIS and remote sensing) to determine the most suitable areas for CSAF.

With the help of geospatial characterization, this study provides valuable insight into the zonal features of the study area and provides valuable information for planning and implementing CSAF practices. 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 unsuitable 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 remote sensing and GIS (Ritung et al., H., 2007; Kihoro et al., 2013; Dengiz, 2013; Yedage et al., 2013; Sarkar et al., 2014; Ayehu and Besufekad, 2015; Reisner et al., 2007).

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 development 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). The cross-site suitability mapping and analysis for CSAF would provide an opportunity to policy-makers for location-specific land use planning for expanding and implementing CSAF-based models. Those would assist in addressing ecosystem restoration, optimum farm production, increased income, and improved food security. 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

The analysis of suitable sites for CSAF in Bugesera and Rulindo was performed using nine variables representing the local climatic, biophysical, and economic features. These variables are the elevation, slope, soil type, rainfall, temperature, LU/LC, distance from road and trade centers, and landslide risks that logically influence the local landscapes. To determine the level of importance of each of these variables, we used the Analytic Hierarchy Process (AHP), and then the weighted overlay analysis was applied to these layers in a GIS platform. Lastly, suitability maps for CSAF systems were generated and analyzed to identify as well as visualize their potential at a comparative cross-site scale.

2.1. Study area

The study area lies on two separate agroclimatic sites of Rwanda i.e., Bugesera and Rulindo regions. Rwanda is a small country located in East Africa and shares its borders in the west with the Democratic Republic of Congo, north with Uganda, east with Tanzania, and south with Burundi (Fig. 1). Rwanda covers an area of 26,338sqkm, largely dominated by highlands, followed by river valleys; while the altitude ranges from 920 to 4,486m 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.

Due to its topography, the average temperature ranges from 16 to 20^{o}C, characterized by two rainy seasons (March-May and September-December) and two dry seasons throughout the year (January-February, and June-August).

Bugesera is located in the Eastern savannah semi-arid lowland zone. The geographic coordinates of this area comprise Latitude 2^{0}09'S and Longitude 30^{0}05'E, whereas the total geographic area is 1,337sqkm (Fig. 2). Since many decades ago, Bugesera has experienced a prolonged period of drought consecutive to its topography and low vegetation. The average temperature oscillates between 26 and 29°C. The elevation varies from 1,100 to 1,780m from the mean sea level. The average annual rainfall is 943mm. As per the Bugesera District Development Strategy (DDS 2018/19-2023/24) (2019), the vegetation of this area is typically dominated by the savannahs' shrubs covering the hills, the grassy savannahs covering the dry valleys and the trays of the hills. The vegetation also is largely composed of acacia trees, euphorbia, and cactuses intertwined with gramineous and spiny bushes. This area is also covered with rare species that are not gigantic but support the bushes and trailing lianas. Additionally, this area is also dominated by undulating hills alternating with dry valleys and marshlands alongside waterbodies.

Rulindo is located in the Temperate zone of the Central Highlands and is mostly characterized by mountains. Rulindo has an area of 567sqkm (Fig. 3) with a tropical climate, characterized by alternating seasons of abundant rainfalls and mild droughts. The geographical coordinates of this area comprise Latitude 1^{o}44'S and Longitude 29^{o}59'E. As per the Rulindo District Development Strategy (DDS 2018/19-2023/24) (2019), the vegetation is largely composed of food crops on hillslopes and valleys with woodland eucalyptus, grevillea, calliandra, and Cyprus. It is also covered with ferns, the elagrostis (ishinge), the latter being a sign of barren and soil degradation. The mean annual temperature is 19°C., while mean rainfall normally reaches 1,243.3mm per year.

2.2. Methodology framework for CSAF land suitability assessment

According to FAO (2007), the framework for land suitability analysis and mapping should be based on an integrative and multidisciplinary approach featuring the criteria of climate (e.g., rainfall, temperature), soil (e.g., type, texture), terrain (e.g., elevation, slope, slope aspect, slope position), LU/LC, landscape patterns, landownership, surface hydrology, ecology (e.g., forest, Normalized Difference Vegetation Index (NDVI)), and socioeconomic (e.g., distance from roads, trade, settlements). Accordingly, we extracted the input variables 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 (Fig. 4).

Based on a group of determinants, the multi-criterion and land suitability modelling were developed to characterize the potential suitable locations for CSAF development in study area. 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. The process followed in this study is illustrated in Fig. 4.

2.3. Assessment of CSAF land suitability in study areas

According to Pramanik (2016), local geological and environmental conditions define land that is suitable for optimum production and transformation. On the other hand, Feizizadeh and Blaschke (2012), Bandyopadhyay et al. (2009), and Kamkar et al. (2014) concur that the identification of suitable sites for agricultural development requires a thorough consideration of the geophysical limitations, topography, and prevailing climate. Per se, various features (biophysical, climatic, socioeconomic) should be considered for the determination of suitability for a novel technology (Wang, 1994; Duc, 2006; Deep and Saklani, 2014). 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 1). Before variable determination, we extensively consulted the literature (Dawit et al., 2020) and visited some parts of the study area in pilot survey. Then, these were mapped using GIS.

Table 1
Study variables used for CSAF land suitability assessment

S/N	Variables	Data Types	Resolution	Source
1	Study area boundaries	Vector data: used to extract the study area boundaries	1:200000	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
2	Rainfall	Raster data: used to extract the mean annual rainfall of the study area	181X181m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
3	Temperature	Raster data: used to extract the mean annual temperature of the meteorological stations in the study area	181X181m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
4	Elevation	Raster data: used to extract the altitude of the study area	30 X 30m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
	Slope	Raster data: used to extract the slope of the study area	30X30m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
5	LU/LC	Raster data: used to extract the LU/LC of the study area	180X180m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
6	Soil type	Raster data: used to extract soil types of the study area	180X180m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
7	ED to roads	Vector data: used to extrapolate distance from roads of CSAF in the study area	181X181m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
8	ED to trade	Vector data: used to extrapolate distance from trade of CSAF in the study area	110X110m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda
9	Landslide risk	Vector data: used to extract erosion hazards of the study area	180X180m	Centre for Geographic Information Systems and Remote Sensing (CGIS) of the University of Rwanda

2.4. Factor mapping using GIS

This step involved utilization of digitized and tabulated data collected from the Centre 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 30m and a digital agroclimatic database containing soil types, temperatures, rainfall, LU/LC, landslide risks, and agroclimatic zones (Fig. 4).

Both study areas (Bugesera and Rulindo) were the basis for the extraction of these files (Fig. 2) 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. 5 & 6).

2.5. 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 (Fig. 7). 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 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 of 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. All the parameters were reclassified into three different categories (Tables 7 & 8).

2.6. Determination of weight for each variable

The Analytic Hierarchy Process (AHP) was used to assign the weight of importance to the selected parameters based on pairwise comparisons according to their relative significance (Miller et al., 1998). AHP was first coined by Saaty (1980). The approach was introduced to establish a hierarchical model for solving complex problems of land use with the options (Malczewski, 2006; Cengiz and Akbulak, 2009; Roig-Tierno et al., 2013). The AHP has been widely used to solve multidimensional problems based on complex parameters across various levels with their interactions (Tiwari et al., 1999).

AHP is applied to a set of variables to build a hierarchical structure by assigning weight to each variable in the decision-making process (Kiker et al., 2005). 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 2).

Table 2
Suggested rating scales for AHP in a pairwise comparison matrix as per Saaty (1987)

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

The pairwise comparison matrix of this study is presented in Table 3. 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 a required threshold level. After concluding this step, the next phase involved the spatial analyses with ArcGIS 10.8 (Fig. 7).

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

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

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

The calculation of the consistency ratio (CR) was done to check the consistency of comparisons in the matrix (Hamere and Teshome, 2018). 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 (Hamere and Teshome, 2018). Accordingly, a CR approaching 1 indicates the probability that rating the matrix was done randomly (Hamere and Teshome, 2018). A computed consistency ration (CR) of 0.1 or less constitutes a reasonable level of consistency (Saaty, 1980; Malczewski, 2000). Results in this study, exhibited a CR of 0.053843448 from the paired comparison matrix between 9 factors, which indicates logical judgment (Saaty, 1980; Malczewski, 2000).

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

$$CI = \frac{\lambda max - n}{n-1}$$ (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):

$$CR = \frac{CI}{RI}$$ (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).

2.7. Suitability model building for CSAF extension in study areas

The land suitability model for CSAF extension in study areas was generated using a weighted overlay approach. The integration of weighted overlay (WO) with the AHP provides an accurate outcome for the site suitability assessment for technology implementation in modern farming (Pramanik, 2016). All created thematic layers were combined in the GIS environment to apply the WO techniques (Girvan et al., 2003). The nine operated raster layers were overlaid by bringing their cell values to the same scale, assigning a weight value to individual variable, and integrating the weight cell values (Eq. 4). The cell values of each raster layer were also multiplied by their weight values (Mojid et al., 2009; Cengiz and Akbulak, 2009) using model builder toolbox of Arc-GIS 10.8 (Fig. 7).

$$S = \sum_{i=0}^{n}(W_i X_i)$$ (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 as suggested by Saaty (1980) and which was similar to the

“Likert-scale” (Lewis and Erdinç, 2017). Obtained classes were termed as follows: “Most suitable, suitable, and Unsuitable”. 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 6.

2.8. 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 separate areas. The final suitability maps were validated through field-visit to collect information on actual CSAF practices in the Bugesera and Rulindo 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. Accordingly, we selected three sites (local administrative entities), 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 (Table 13).

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

3. Results and Discussion

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

The computation of CI was done as follows: $CI = (\lambda max - n) / (n - 1)$ (Hamere and Teshome, 2018) with λmax: 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 5). The derived $\frac{CI}{RI}$ ratio, called the Consistency Ratio (CR), was also obtained (Table 4). To validate the matrix and the weights obtained for each factor, a threshold as suggested by Saaty (1980) was adopted, i.e., 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 4) 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.

Table 3
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									
Source: Primary data, 2023									

This approach has effectively and extensively been adopted for land suitability evaluation since the mid-1990s (Feizizadeh et al., 2017; Nouri et al., 2017; Jamil et al., 2018; Ebrahimi et al., 2019). According to Khahro et al. (2014), AHP together with weighted overlay analysis, has been a useful approach to generate tangible results for agriculture land suitability evaluation.

Table 4
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%											
Source: Primary data, 2023											

Both biophysical and socioeconomic factors inherent to CSAF practices were classified (Table 4) using biophysical and economic constraints and weights were attributed based on Saaty (1980)'s AHP in Table 3. The results computed in Table 4 were used as inputs in building suitability maps for CSAF.

Table 5
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 6 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 most suitable and favorable conditions for adaptability and CSAF scaling up. The results computed in Table 6 were then utilized in the GIS model environment (Fig. 6) to classify variables and for the final WO.

Table 6
Weight matrix of variables for suitability mapping in study areas

Variables	Weight (%)	Value/Description	Ranks	Suitability
Elevation	30	< 1000m	3	Most suitable
		1000-1500m	2	Suitable
		> 1500m	1	Unsuitable
Slope	19	< 10%	3	Most suitable
		10–25%	2	Suitable
		> 25%	1	Unsuitable
Soil	16	Clay	1	Unsuitable
		Gravel	2	Suitable
		Sand	3	Most suitable
Rainfall	10	< 1000mm	1	Unsuitable
		1000-1100mm	2	Suitable
		> 1100mm	3	Most suitable
Temp	9	< 15^{o}C	3	Most suitable
		15-20^{o}C	2	Suitable
		> 20^{o}C	1	Unsuitable
Land	5	Settlement	3	Most suitable
		Agriculture	2	Suitable
		Forest	1	Unsuitable
Landslide risk	4	Grid code: 4	3	Most suitable
		Grid code: 5	2	Suitable
ED to road (km)	5	< 1km	3	Most suitable
		1-5km	2	Suitable
		> 5km	1	Unsuitable
ED to trade (km)	2	< 1km	3	Most suitable
		1-5km	2	Suitable
		> 5km	1	Unsuitable
Source: Primary data, 2023				

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

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 4 which was generated in pairwise comparisons process (Saaty, 1980), a widely accepted statistical tool in GIS mapping (Sarkar et al., 2014). Table 7 presents classes for each variable selected for the CSAF land suitability analysis for Bugesera. The area in hectares and the relative values (percentages) of classes were determined based on the total surface of the study area.

We found that for elevation, almost 40% (50,033.25ha) of Bugesera was classified as most suitable for CSAF (< 1000m), and 42.8% (52,435.89ha) was suitable (1000-1500m). For the slope, only 8.46% (10,314.81ha) of the area was unsuitable (>25%) for the CSAF extension. The dominant soil types were clay classified as unsuitable (53.27%) and sand being the most suitable (31.98%). Clay was classified as unsuitable because soils with high clay content are impenetrable to water and air and nutrient substances. Hence, clay soils can be difficult for the penetration of roots and the germination of plants, and can be very hard for farmers to till. Slightly above half (55.49%) of the area was classified as close to the roads (<1 km) and was considered as most suitable for CSAF. Regarding the distance from trading centers, 36.94% (47,671.58ha) were classified as most suitable because they are located at < 1km. 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% (40,227.23ha) and 31.19% (40,040.49ha) were presented as the most suitable land, respectively. Suitability maps of these nine classification variables are presented in Fig. 8.

Table 7
Variables used in suitability analysis for CSAF in Bugesera

Variables	Suitability	Classes	#Pixels	Area (ha)	Area (%)
Elevation	Most suitable	< 1000m	555925	50033.25	40.91
	Suitable	1000-1500m	582621	52435.89	42.87
	Unsuitable	> 1500m	220444	19839.96	16.22
Slope	Most suitable	< 10%	700766	63068.94	51.76
	Suitable	10–25%	538553	48469.77	39.78
	Unsuitable	> 25%	114609	10314.81	8.46
Soil type	Unsuitable	Clay	19884	64424.16	53.27
	Suitable	Gravel	5507	17842.68	14.75
	Most suitable	Sand	11936	38672.64	31.98
Rainfall	Unsuitable	< 1000mm	12279	40227.23	31.18
	Suitable	1000-1100mm	14488	47464.14	36.78
	Most suitable	> 1100mm	12619	41341.11	32.04
Temperature	Most suitable	< 15°C	12222	40040.49	31.19
	Suitable	15-20°C	14489	47467.41	36.97
	Unsuitable	> 20°C	12479	40882.45	31.84
LU/LC	Most suitable	Settlement	2482	8041.68	7.61
	Suitable	Agriculture	24554	79554.96	75.25
	Unsuitable	Forest	5594	18124.56	17.14
ED to roads	Most suitable	< 1km	21854	71595.89	55.49
	Suitable	1-5km	14488	47464.14	36.79
	Unsuitable	> 5km	3040	9959.34	7.72
ED to trade	Most suitable	< 1km	39398	47671.58	36.94
	Suitable	1-5km	45526	55086.46	42.68
	Unsuitable	> 5km	21737	26301.77	20.38
Landslide	Most suitable	High	1069	3463.56	100
Source: Primary data, 2023					

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 the successful development of tree raising on farm systems.

3.3. Standardized suitability maps of thematic layers for CSAF in Rulindo

Table 8 and Fig. 9 present classes for each variable used for the CSAF land suitability analysis in Rulindo. Results showed that for elevation, 17.55% (623.52km2) area lies on lower elevation which is most suitable for CSAF. Regarding the slope, slightly above half (52.45%) of the land area is most suitable for CSAF on gentle slopes (< 10%). The dominant soil types were clay classified as unsuitable (49.07%) and sand being the most suitable (25.57%). More than half (61.47%) of the area was classified as close to the roads (<1 km) and was considered as most suitable for CSAF. Regarding the distance from trading centers, 32.04% (15,307.71ha) was classified as most suitable because they are located at < 1km. For rainfall and temperature, 32.91% (42,576.19ha) and 12.4% (16,046.34) were presented as the most suitable land, respectively. It was 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. The details are given in Table 8.

High elevation (>1500m), and steep slope (>25%) with higher intensity of erosion were common characteristics, resulting in a lower rate of most suitable CSAF in Rulindo. Akinci et al. (2013) found similar results, as a lower rate of 0.4% area for highly suitable agriculture was computed, in a study of agricultural land suitability evaluation for the hilly areas of Ispir, Erzurum (Turkey).

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.

In 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). Large dams and reservoirs with entire drainage systems can cause conflictual interests in the local communities as they affect immediate agricultural lands, cultural heritage, and settlements (Bhutia, 2014).

Table 8
Variables used in land suitability analysis for CSAF in Rulindo

Variables	Suitability	Classes	#Pixels	Area (ha)	Area (%)
Elevation	Most suitable	< 1000m	6928	623.52	17.55
	Suitable	1000-1500m	18603	1674.27	47.11
	Unsuitable	> 1500m	13957	1256.13	35.34
Slope	Most suitable	< 10%	311048	27994.32	52.45
	Suitable	10–25%	211931	19073.79	35.73
	Unsuitable	> 25%	70084	6307.56	11.82
Soil type	Unsuitable	Clay	19289	62496.36	49.07
	Suitable	Gravel	9969	32299.56	25.36
	Most suitable	Sand	10055	32578.20	25.57
Rainfall	Unsuitable	< 1000mm	12996	42576.19	32.91
	Suitable	1000-1100mm	18801	61593.96	47.61
	Most suitable	> 1100mm	7691	25196.48	19.48
Temperature	Most suitable	< 15^{o}C	4898	16046.34	12.4
	Suitable	15-20^{o}C	15683	51379.08	39.72
	Unsuitable	> 20^{o}C	18907	61941.22	47.88
LU/LC	Most suitable	Settlement	5660	18338.40	14.39
	Suitable	Agriculture	6273	20324.52	15.96
	Unsuitable	Forest	27381	88714.44	69.65
ED to roads	Most suitable	< 1km	24272	79517.50	61.47
	Suitable	1-5km	11705	38346.75	29.64
	Unsuitable	> 5km	3511	11502.39	8.89
ED to trade	Most suitable	< 1km	12651	15307.71	32.04
	Suitable	1-5km	16181	19579.01	40.98
	Unsuitable	> 5km	10656	12893.76	26.98
Landslide	Most suitable	Low	12651	40989.24	32.04
	Suitable	High	16181	52426.44	40.98
	Unsuitable	Very high	10656	34525.44	26.98
Source: Primary data, 2023					

The combination of the nine variables to determine land suitability for CSAF in Bugesera and Rulindo is presented in Figs. 10 and 11, respectively. 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.

3.4. Generation of suitability map for CSAF in Bugesera

The statistics in Table 9 show that 1.60% (1,662.82ha) of Bugesera is most suitable and 86.62% (90,123.78ha) is suitable for CSAF. While 11.78% (12,262.50ha) represent unsuitable land for CSAF. Figure 10 shows that the agricultural zones which are suitable and most suitable for CSAF cover almost all sectors of Bugesera (88.22%), a rural area largely agrarian. The remaining area of CSAF unsuitability (11.78%) is more categorized as soils hit by prolonged drought, water bodies, marshlands, forests, and bushlands. Unsuitable land 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, Ntarama and Mwogo alongside Nyabarongo river in northern, Nyamata, Mayange and Ngeruka in Central and Kamabuye in southern. For increased agricultural production, the ongoing and future CSAF schemes can be diverted to suitable and most suitable areas identified in this study mainly dominated by arable land.

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

Suitability	#Pixels	Area (ha)	Area (%)
Unsuitable	3702	12262.50	11.78
Suitable	27208	90123.78	86.62
Most suitable	502	1662.82	1.60
Source: Primary data, 2023			

3.5. Generation of suitability map for CSAF in Rulindo

The statistics in Table 10 show that 9.69% (709.92ha) of Rulindo is most suitable and 88.92% (6,514.56ha) is suitable for CSAF. While 1.39% (102.24ha) represent unsuitable land for CSAF. Figure 11 shows that the areas identified as suitable and most suitable for CSAF cover the major part of Rulindo (98.61%) which is rural and largely agrarian. The remaining area of CSAF unsuitability (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 suitable or most suitable for CSAF. In short, zones of the most suitability and suitability level should therefore be privileged in expanding the CSAF pratcices in Rulindo.

Table 10
Areal distribution of land suitability analysis results for CSAF in Rulindo

Suitability	#Pixels	Area (ha)	Area (%)
Unsuitable	71	102.24	1.39
Suitable	4524	6514.56	88.92
Most suitable	493	709.92	9.69
Source: Primary data, 2023			

In the Bugesera and Rulindo zones of Rwanda, the potential for CSAF is often hampered by a lack of suitable soils characterized by soil degradation occasioned by large-scale deforestation (timber, firewood, and charcoal) and shifting cultivation into marginal lands due to land scarcity. Hence, to address the problem of soil and environmental losses, and the decline in farm productivity, suitable CSAF can be initiated in the affected zones following the approach laid down in this study.

3.6. Cross-site comparative analysis

As shown in the summary statistics, the available means suitable land for CSAF is 34,683.03ha in Bugesera (34,683.03 ± 48,304.71) and 2,442.24ha in Rulindo (2,442.24 ± 3,539.79) (Table 11). The SD is larger in both sites and amply suggests that this was due to larger variation in the data with a range of 88,460.95ha (1,662.82 — 90,123.78ha) in Bugesera and 6,412.32ha (102.24 — 6,514.56ha) in Rulindo.

Table 11
Summary statistics to the data frame

Statistics	**Bugesera**	**Rulindo**
Mean	34683.03	2442.24
SE	27888.74	2043.70
Median	12262.50	709.92
Variance	2333345286.77	12530161.38
Standard deviation	48304.71	3539.79
Range	88460.95	6412.32
Minimum	1662.82	102.24
Maximum	90123.78	6514.56
Sum	104049.11	7326.72
Source: Primary data, 2023		

As shown in Table 12, land suitability scores for CSAF largely varied across sites (F = 1.33, p = 0.31).

Table 12
ANOVA summary output to the data frame

Source	**SS**	**df**	**MS**	**F**	**P**
Between Groups	1559203415.86	1	1559203415.86	1.33	0.31
Within Groups	4691750896.31	4	1172937724.08		
Total	6250954312.17	5			
Source: Primary data, 2023					

The proportions of suitable areas for CSAF varied with sites in the study areas of Bugesera and Rulindo (Fig. 12). Most suitable zones were observed in Bugesera for 1,662.82ha (1.6%) against 709.92ha (9.69%) in Rulindo, suitable areas observed in Bugesera were 90,123.78ha (86.62%) against 6,514.56ha (88.92%) in Rulindo while unsuitable areas observed in Bugesera were 12,262.50ha (11.78%) against 102.24ha (1.39%) in Rulindo.

Despite the lack of availability of data on CSAF in Rwanda, results showed that CSAF is well-positioned in Bugesera and Rulindo to tackle land degradation while safeguarding biodiversity. If the developed map models are consulted in the agrarian zones of Bugesera and Rulindo, the impact will be huge for sustainable land use in these regions. Moreover, local peoples utilize local means such as traditional land tillage tools, and farmyard manure, build terraces, and carry out small-scale agricultural production on lands that are unsuitable for agricultural production (Pramanik, 2016). The support, promotion, and scaling up of need-based locally suitable farming practices involving CSAF would improve productivity, and food security, support local biodiversity, and mitigate climate change (Mishra et al., 2018). Hence, putting together suitability assessments with other resource evaluations can help promote better land stewardship while meeting production goals.

Our findings concur with Bentrup and Leininger (2002) who asserted that depending on the scale of analysis, suitability assessments can serve in the design, adoption, promotion, and planning of tree-based farming systems. For Bentrup and

Leininger,(2002), suitability assessment 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. 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 e.g., in highly erodible lands.

Cross-site level analyses or local assessments would help in developing technology transfer programs such as extension services, publications, and farmer field schools (FFS) on CSAF. These assessments are also helpful in deciding whether it is practicable to establish processing facilities or value chains to market and distribution of specialty products. Finally, results from land suitability evaluations may contribute to the academic discourse of CSAF in universities and research institutes dedicated to finding viable alternatives for farmers.

3.7. 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)) (Figs. 13 & 14). 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 unsuitable class. These unsuitable locations, 1 point (about 9%), were found in the Bushoki sector (Rulindo) at 2,108.647m of altitude classified as an “unsuitable” 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 13.

Table 13
Matching field results with model-derived classes for CSAF

On-farm arrangement practices	Model-derived CSAF suitability class				
	Most suitable	Suitable	Unsuitable	Total	Matching (%)
Home-garden	3	0	0	3	100
Alley cropping	2	3	1	6	83
Plantation-crop combination	2	0	0	2	100
Source: Primary data, 2023					

4. Conclusion

The geospatial characterization of CSAF in Bugesera and Rulindo regions in Rwanda as a case study provides valuable insights into the extent of distribution and composition of CSAF systems in these parts of the country. The main objective of this study was to assess the potential land suitability of the two separate zones for CSAF development 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). AHP and GIS were utilized to evaluate the nine selected variables. The approach consisted in transforming numerical data with different magnitudes into suitability classes. The suitability surface for CSAF was obtained by integrating the various factors into the GIS. Thus, based on their surface values, they were classified into three CSAF suitability classes (most suitable, suitable, and unsuitable).

The results of the study show that CSAF systems are prevalent in these two zones (Bugesera and Rulindo), with varied tree species identified across the study area. The study also found that the majority of CSAF systems in the two places are multistrata systems, which provide multiple benefits such as soil fertilization, increased biodiversity, and reduced GHG emissions.

As computed, the *most suitable* areas comprise 1,662.82ha and 709.92ha in Bugesera and Rulindo, respectively. These areas exhibit healthy soils, adequate rainfall as well as gentle slopes, and low elevation, a source of adequate favorable conditions for CSAF technologies. In the absence of soil erosion, the soil fertility in these areas is high and may be best suitable for crop production, horticultural systems, and tree growing.

As computed, the *suitable* areas comprise 90,123.78ha and 6,514.56ha in Bugesera and Rulindo, respectively. They exhibit medium elevation, moderate slope, medium healthy soils, moderate temperature, and moderate rainfall which provide balanced favorable conditions for the CSAF practices. They encompass the largest fraction of the arable land for both sites (Bugesera and Rulindo). These sites generally have average soil fertility and insufficient soil moisture, and due to moderate topography, signs of soil erosion are common. These areas are suitable for plantation purposes for a few land conservation tree species such as Grevillea robusta, calliandra, and Alnus.

As computed, *unsuitable* zones for CSAF account for 12,262.50ha and 102.24ha in Bugesera and Rulindo, respectively. They show poor soils, high elevation, steep slopes, and low rainfall which provide the least favorable conditions for cultivation and tree growing. They mostly comprise highly exposed rocks with no topsoil (low organic matter) with eroded sloppy land. As such, these areas can be transformed into productive soils after rehabilitation and improvements.

These results provide valuable information for understanding the current status and potential of CSAF in these two areas. In areas such as Bugesera and Rulindo where investigations on CSAF are scanty, suitability maps in this study would allow identifying sites with high potential for CSAF. The cross-site suitability mapping and analysis for CSAF would provide an opportunity to policy-makers for location-specific land use planning for expanding and implementing CSAF-based models. Those would assist in addressing ecosystem restoration, optimum farm production, increased income, and enhanced food security. This study will pave the way for further studies on the potential CSAF and possibly required interventions for the assessed areas.

Declarations

CRediT authorship contribution statement

Donatien Ntawuruhunga: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft preparation, Software, Writing – review and editing, Visualization. **Edwin E. Ngowi:** Writing – original draft, Methodology, Data curation, Validation, Writing – review and editing, Visualization, Supervision. **Halima O. Mangi:** Writing – original draft, Methodology, Data curation, Validation, Writing – review and editing, Visualization, Supervision. **Raymond J. Salanga:** Writing – original draft, Writing – review and editing, Project administration, Supervision. **Kelvin M. Shikuku:** Writing – original draft, Methodology, Data curation, Validation, Writing – review and editing, Visualization, Supervision. All authors have read and agreed to the published version of the manuscript.

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Declaration of Interest

None.

Data Availability

Data will be made available on request.

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Figures

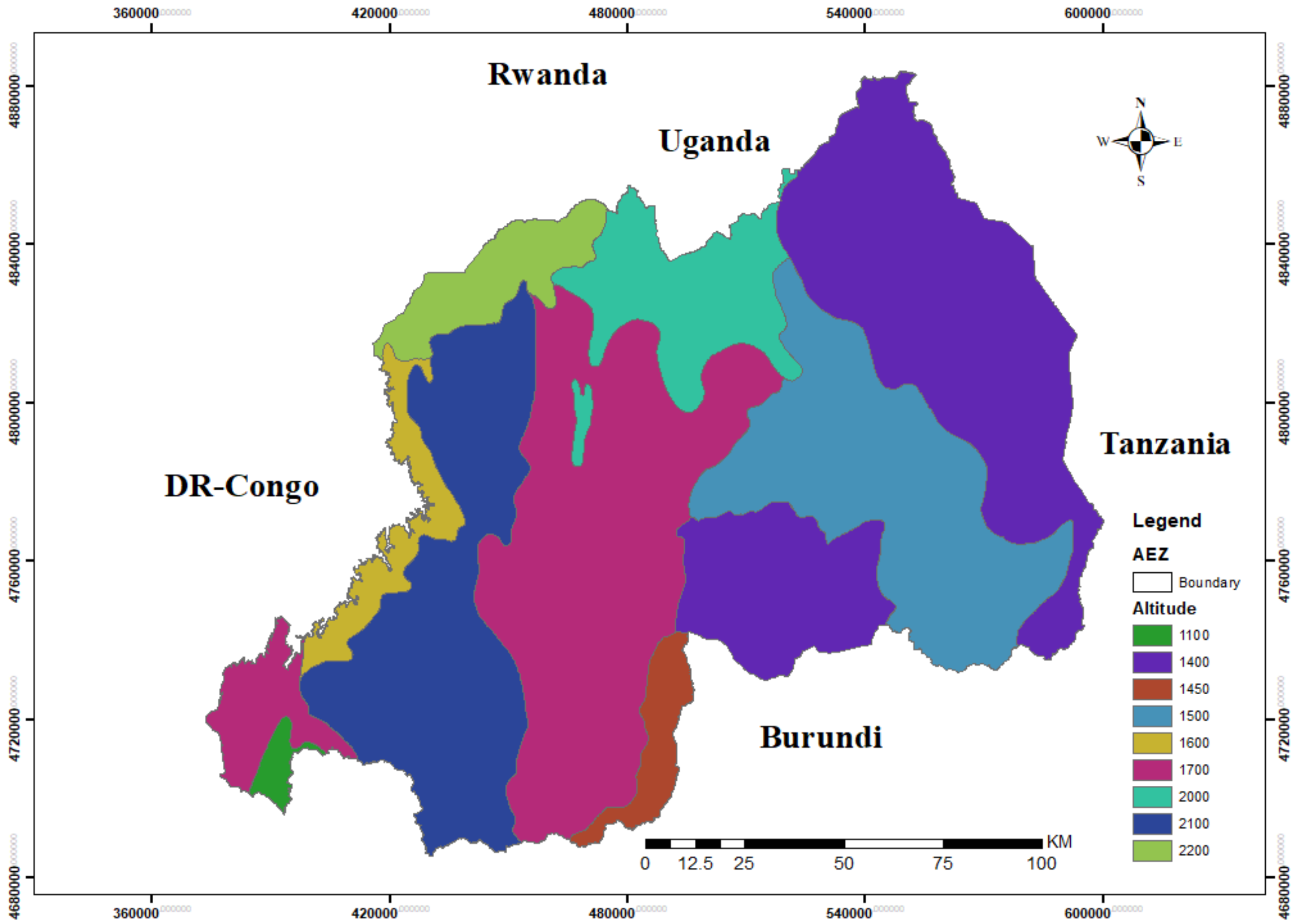

Figure 1

Agroecological zones of Rwanda

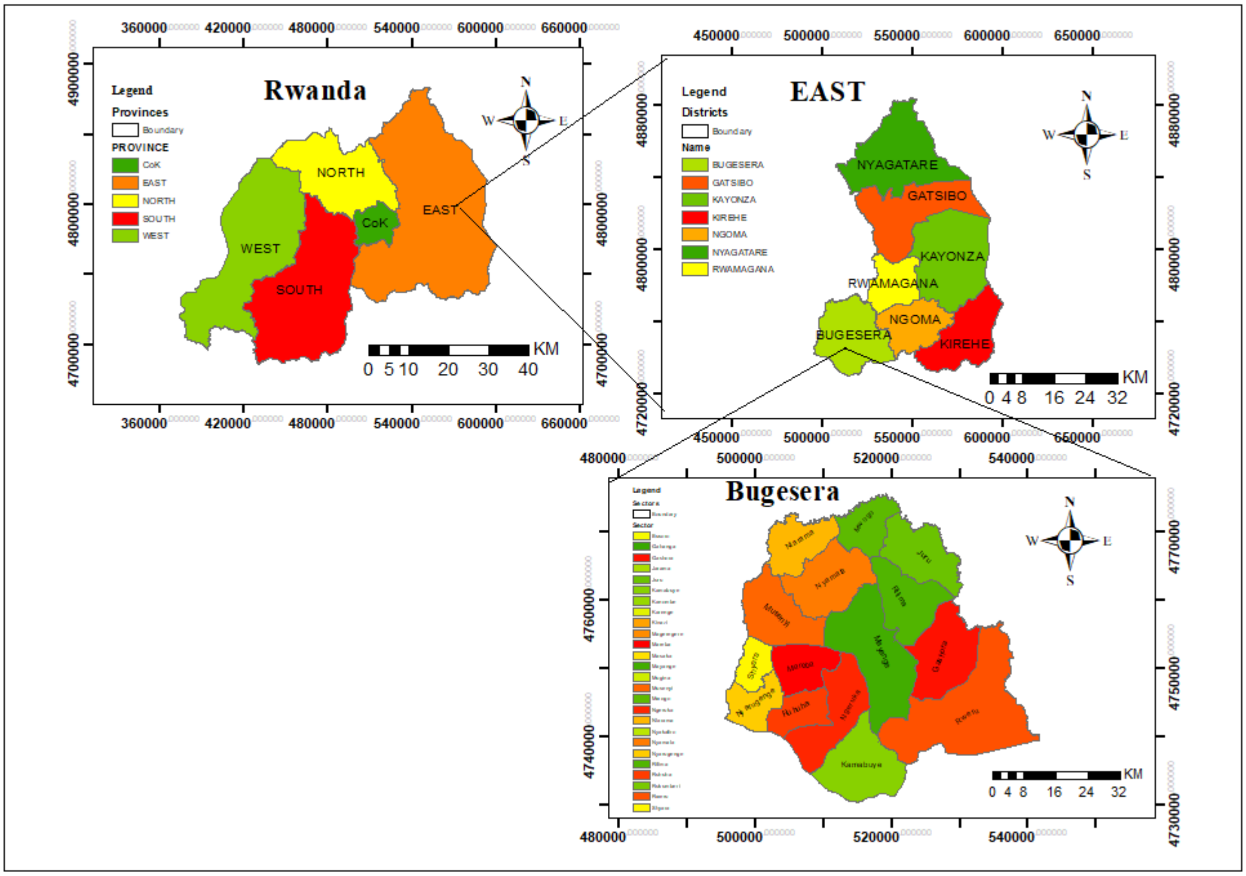

Figure 2

Location of field study (Bugesera: adapted after CGIS)

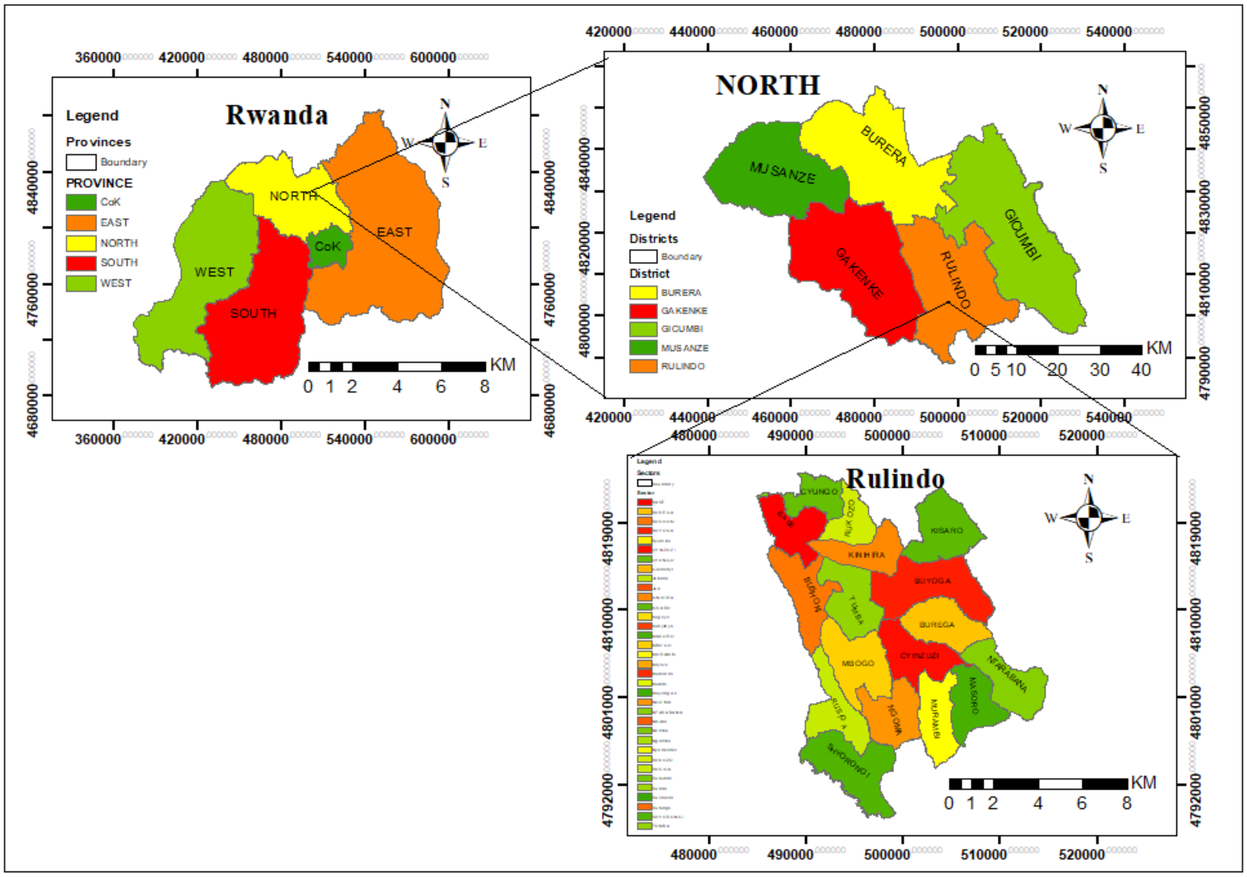

Figure 3

Location of field study (Rulindo: adapted after CGIS)

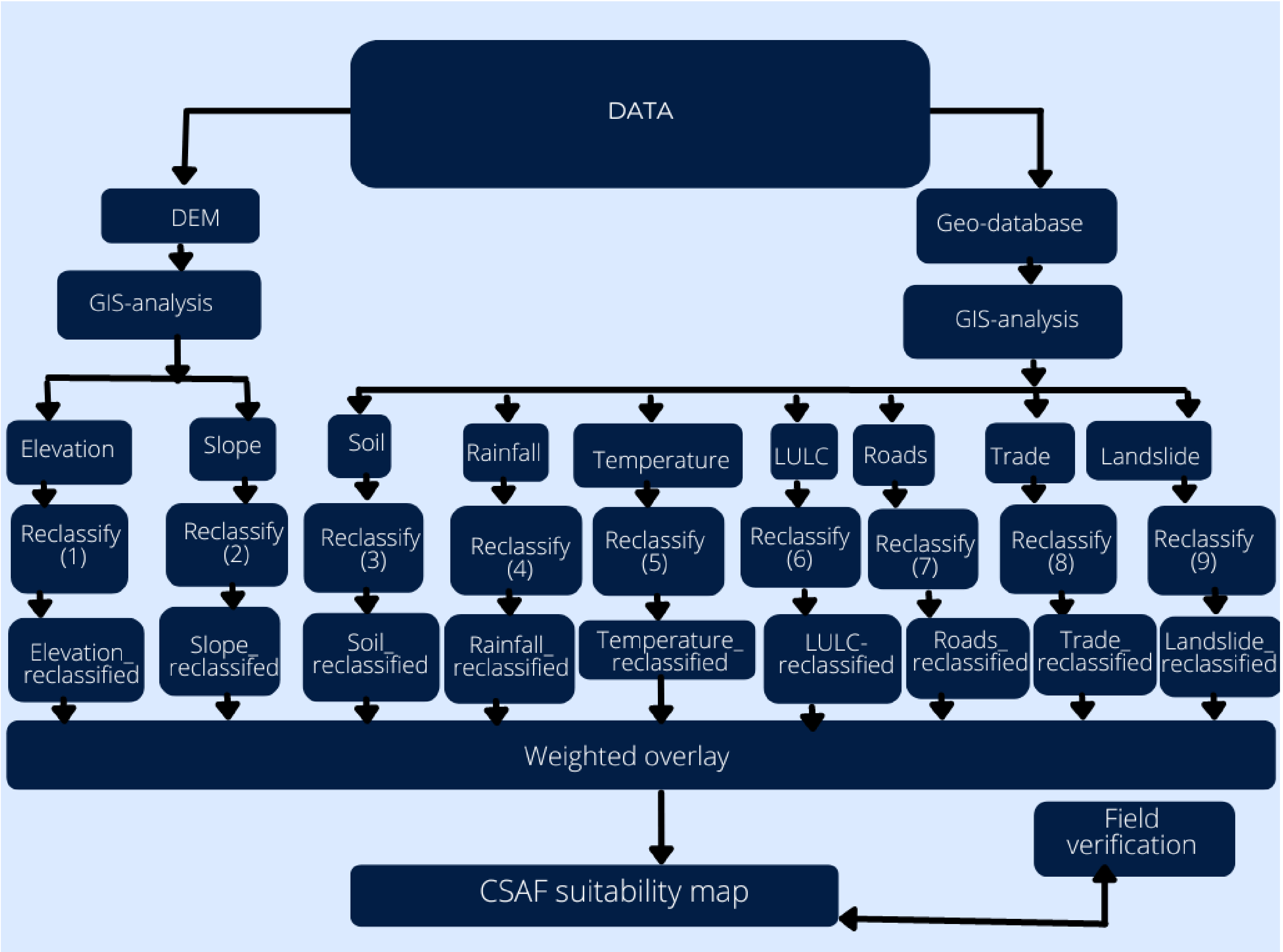

Figure 4

Methodology workflow

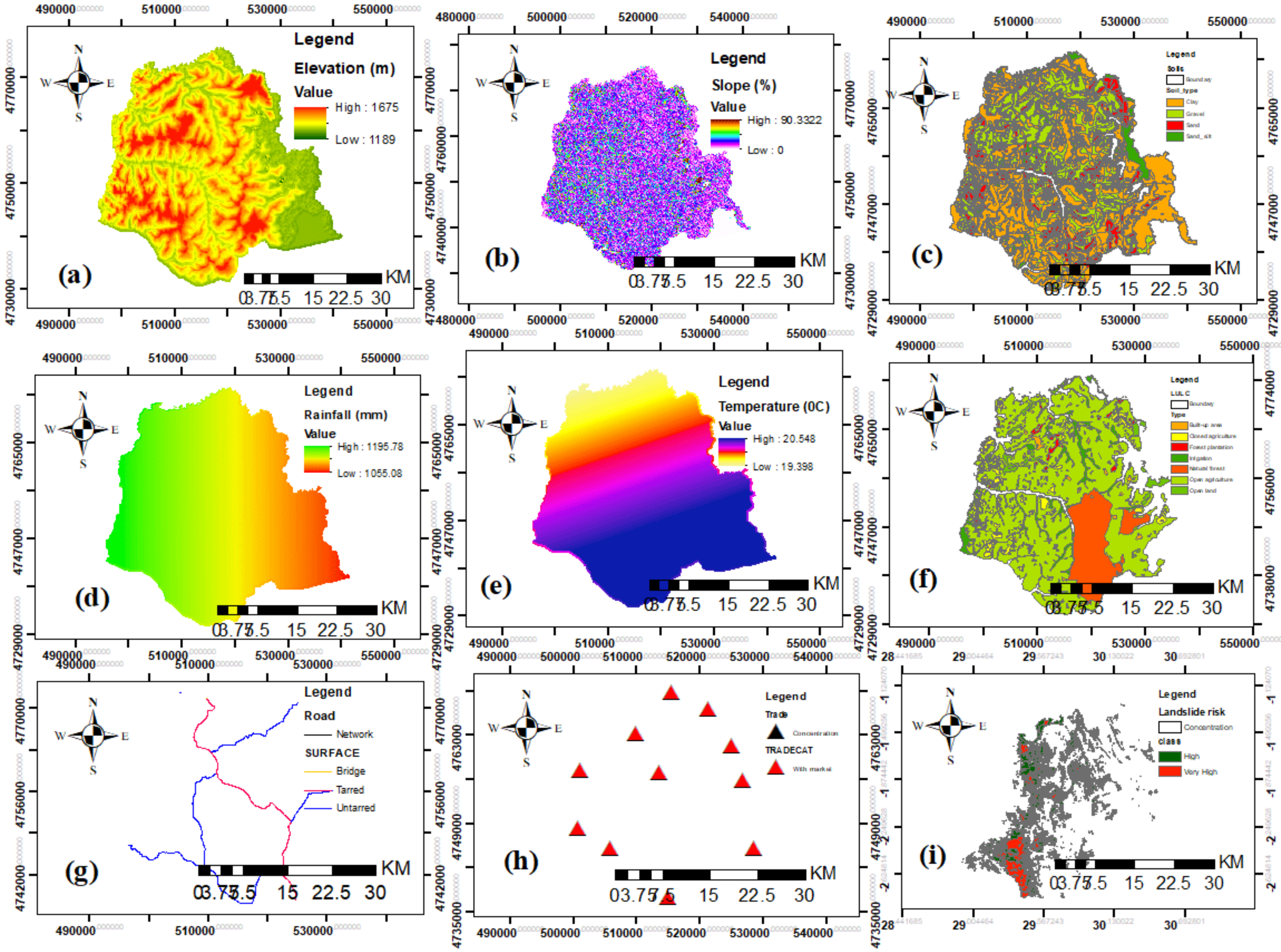

Figure 5

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

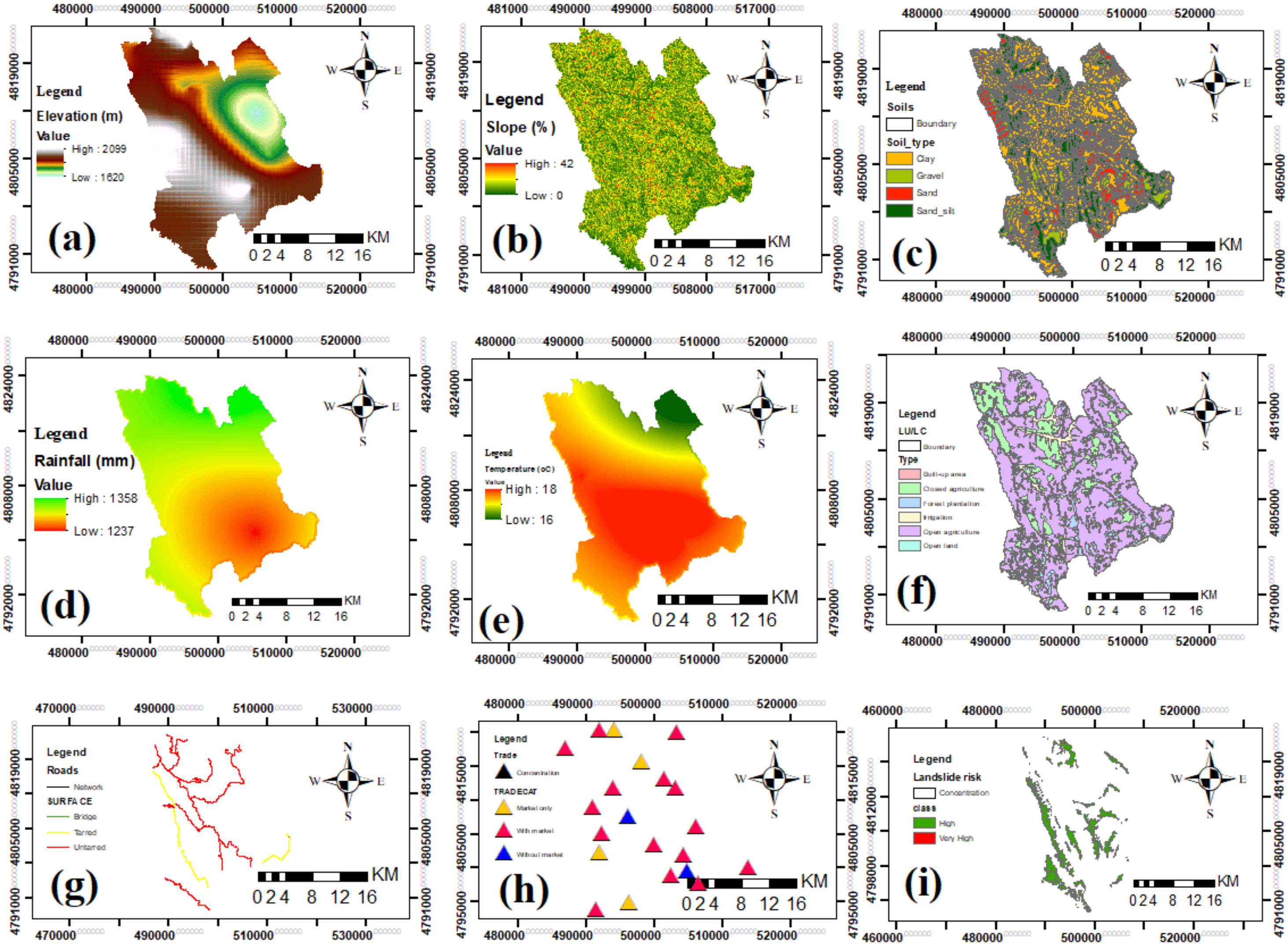

Figure 6

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

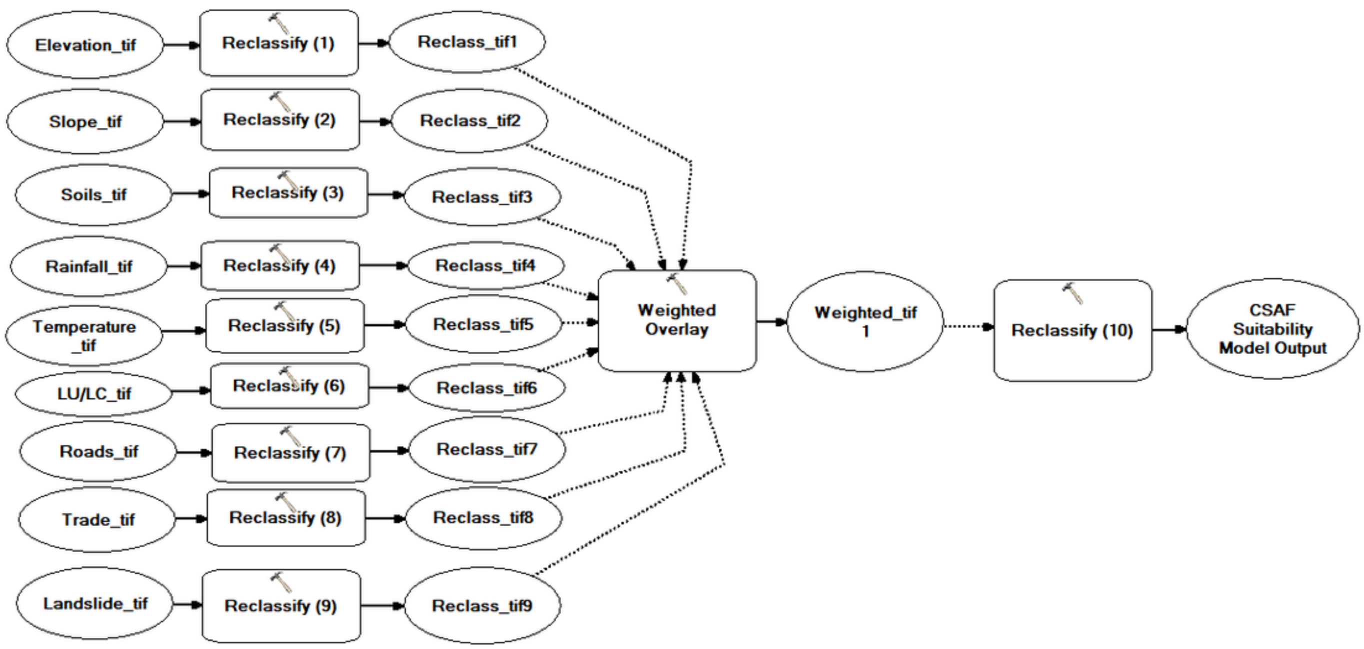

Figure 7

The land suitability model for CSAF

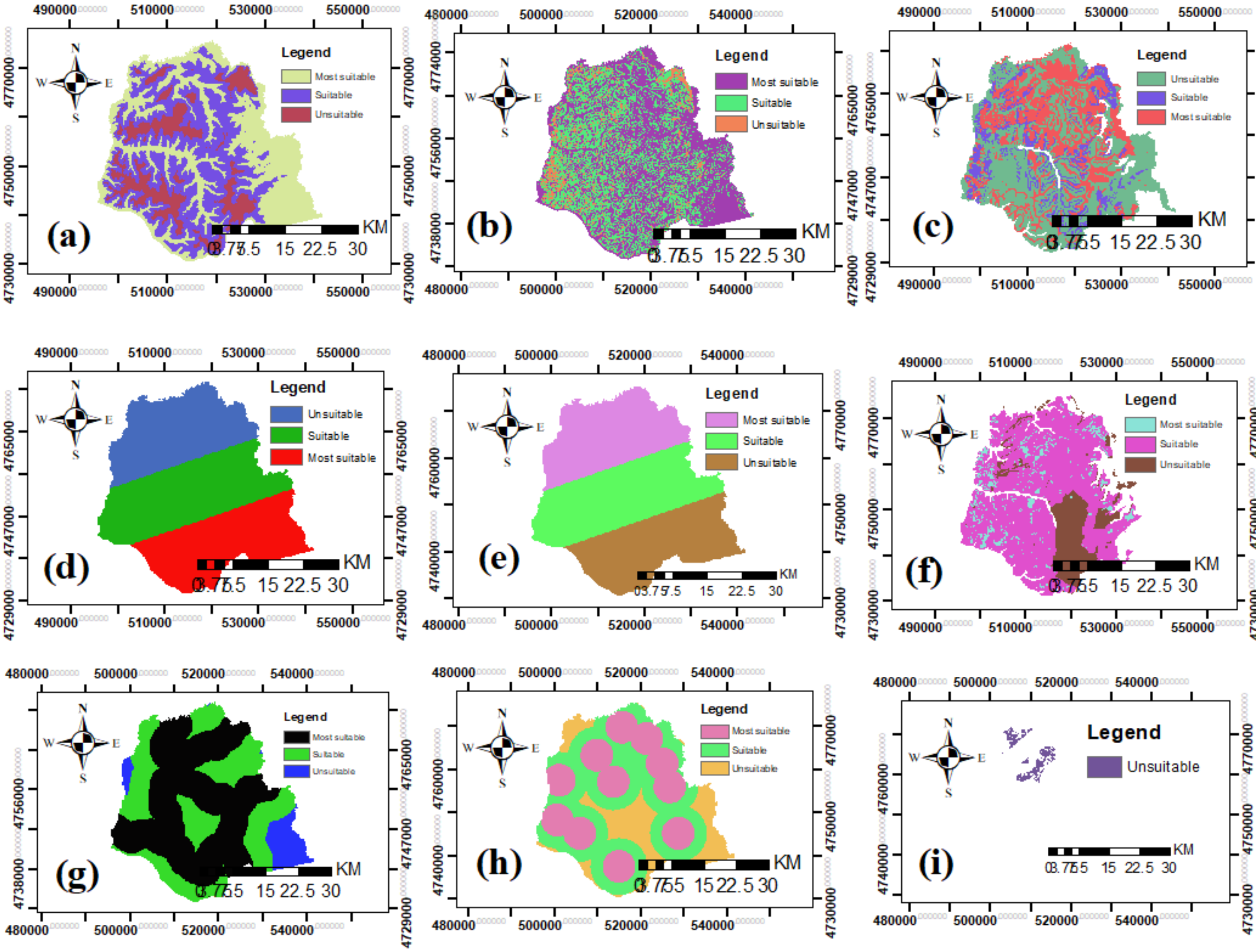

Figure 8

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

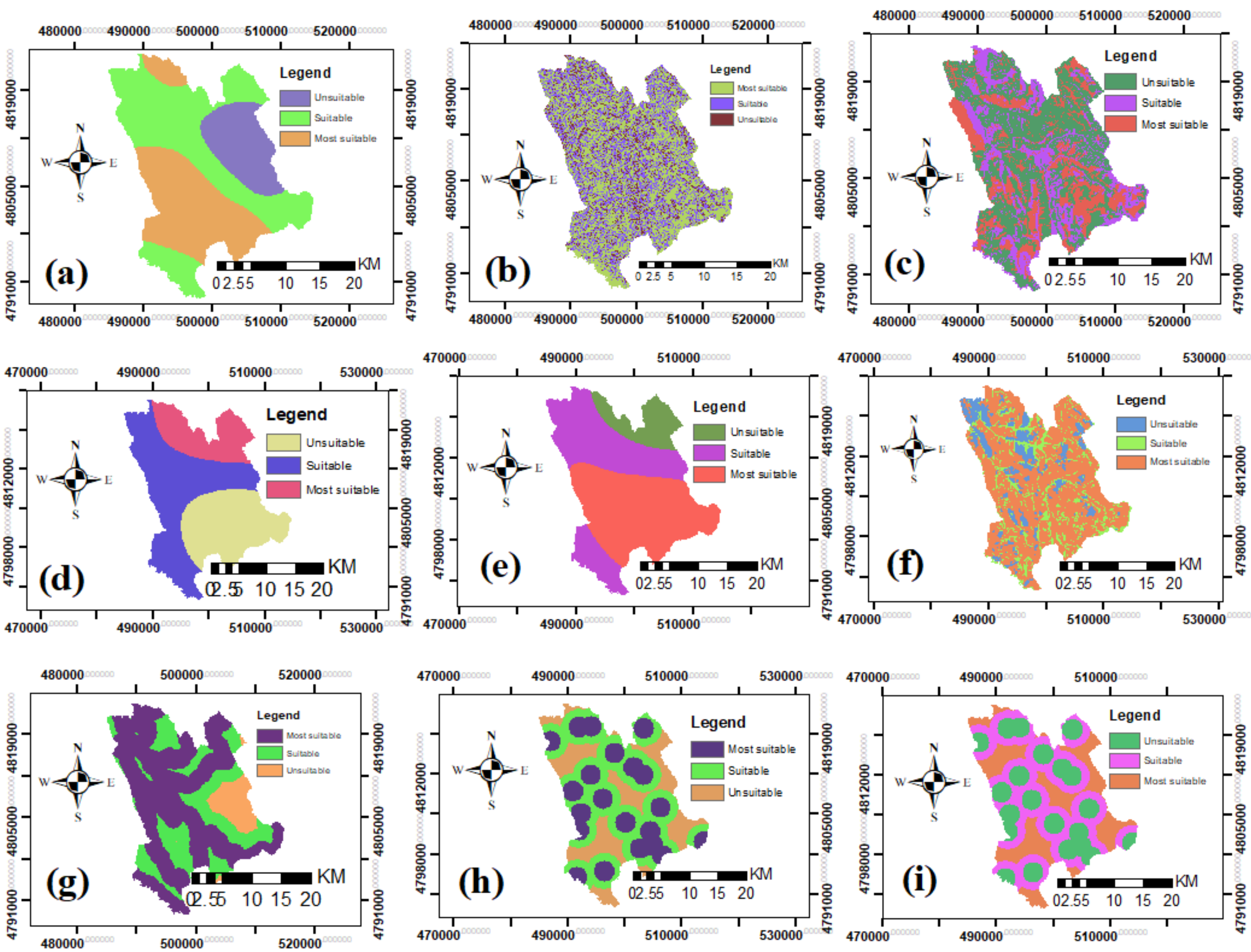

Figure 9

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

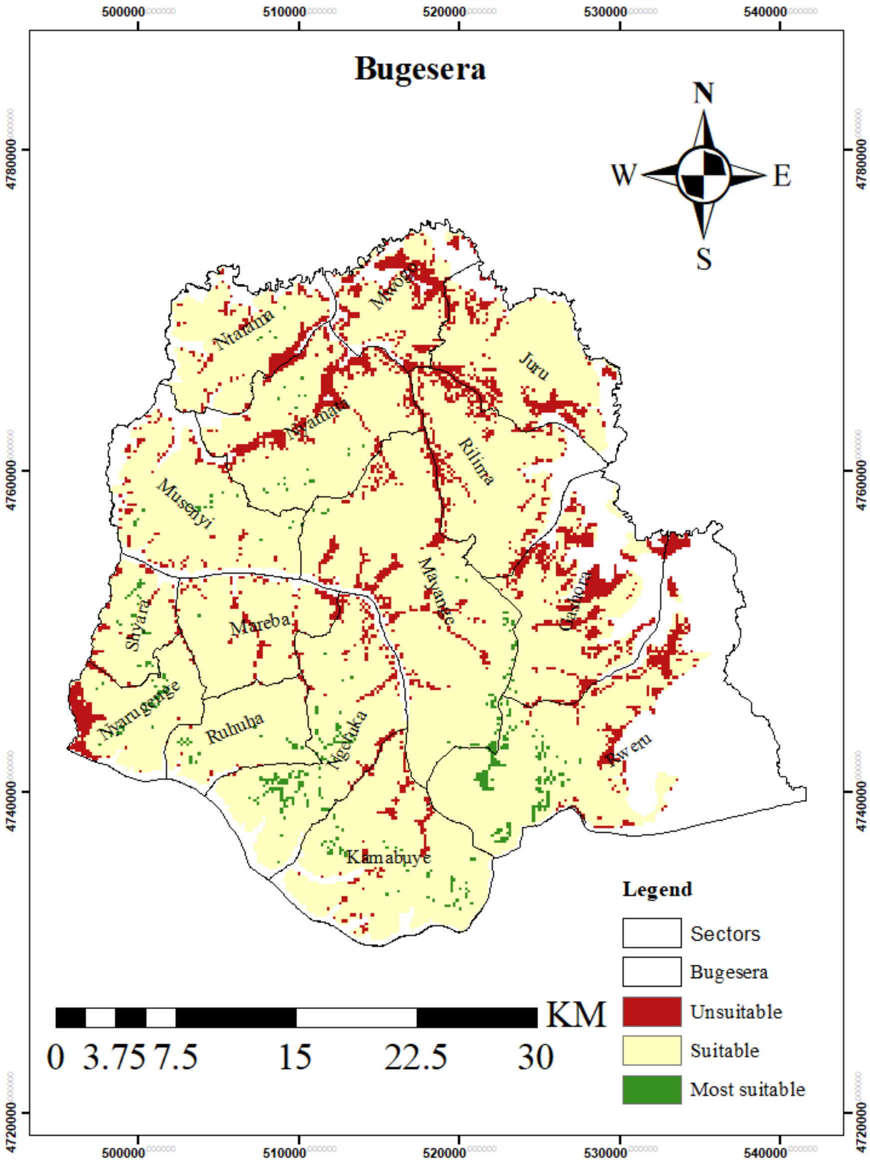

Figure 10

Bugesera composite CSAF suitability map

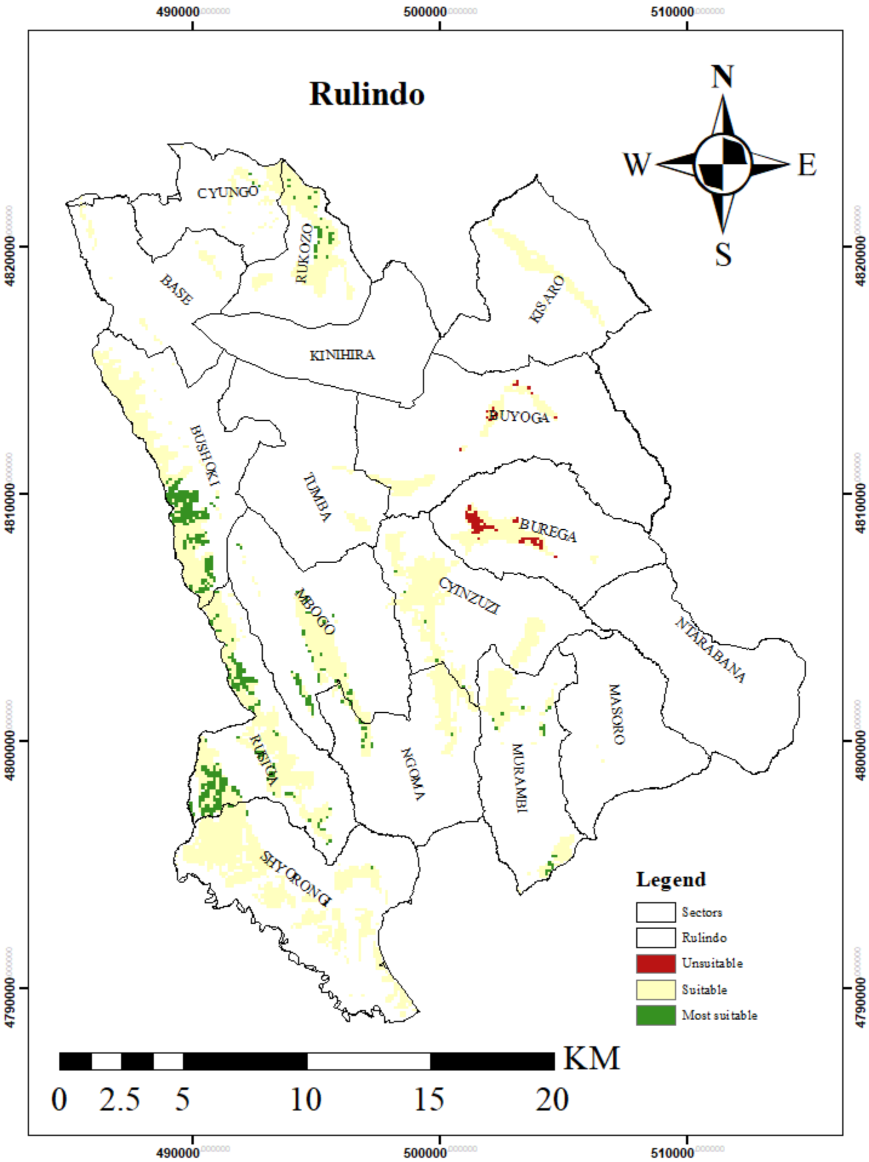

Figure 11

Figure 12. Rulindo composite CSAF suitability map

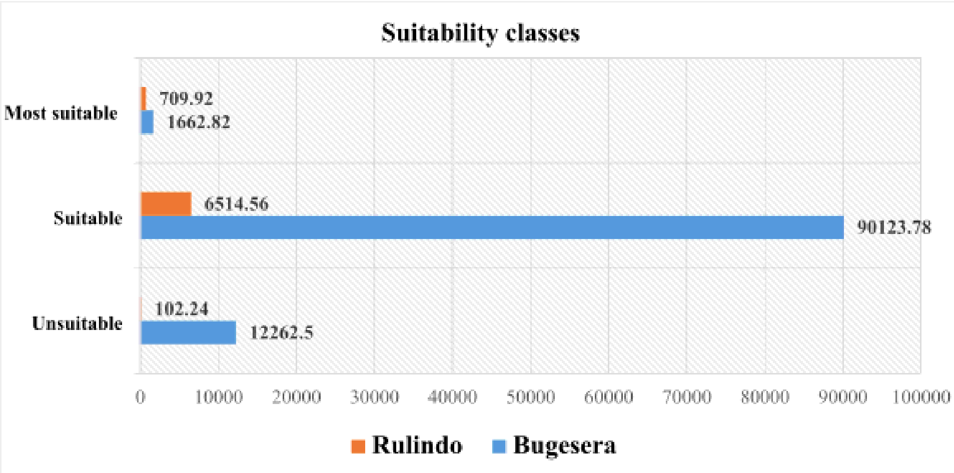

Figure 12

Figure 13. Variation of suitability classes for CSAF (value above each bar denotes the area (ha))

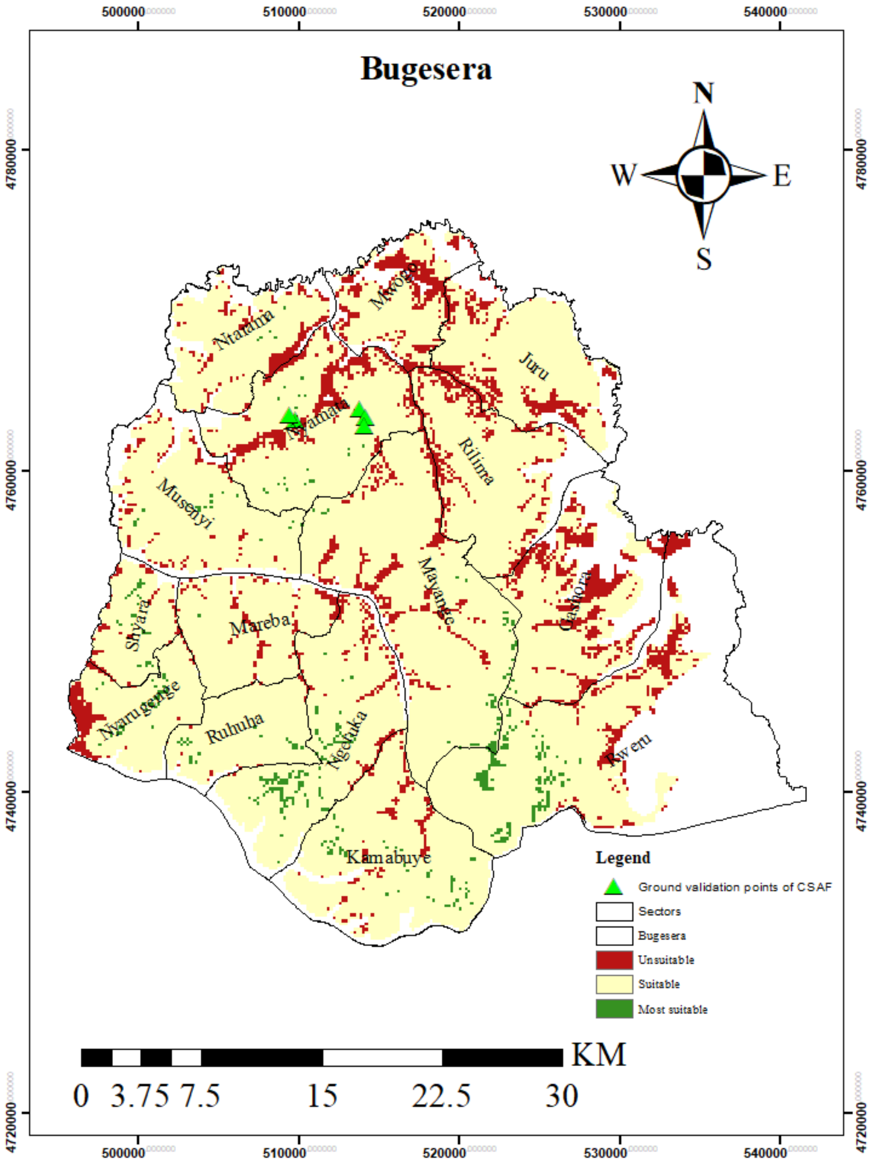

Figure 13

Figure 14. GPS-based ground validation points of CSAF in Bugesera

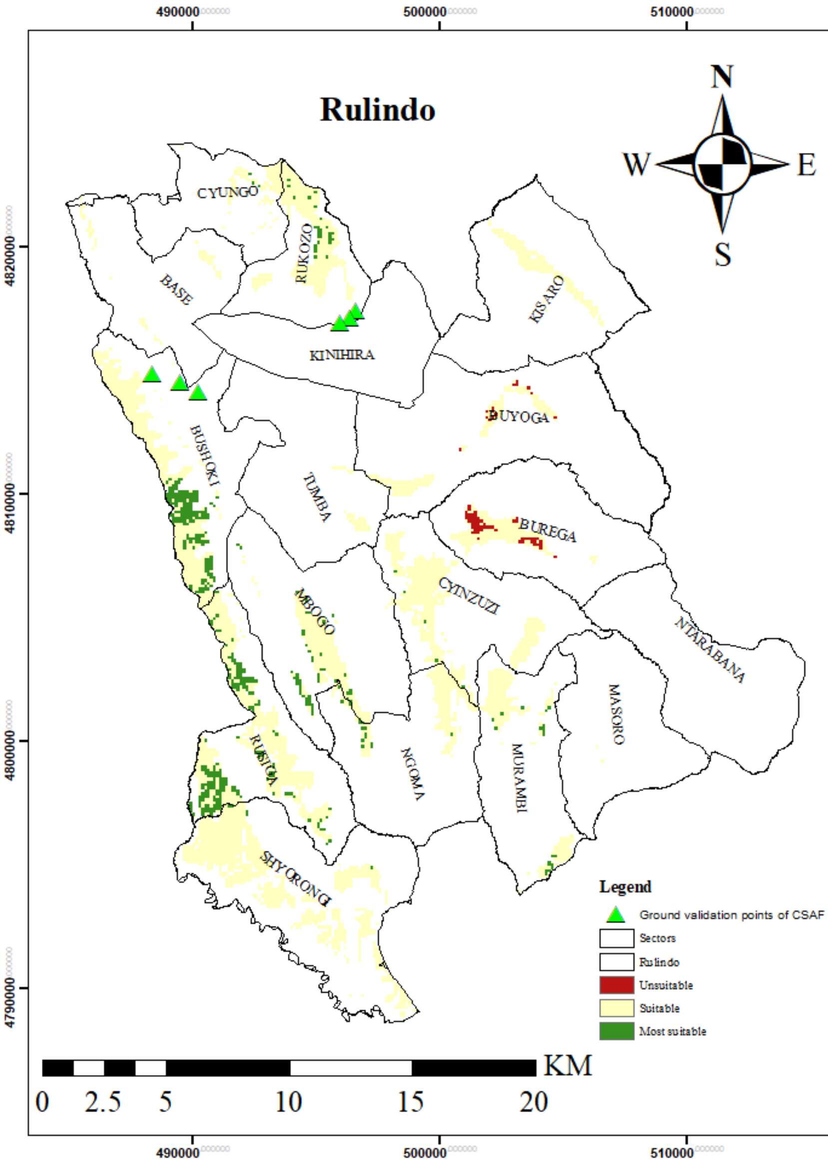

Figure 14

Figure 15. GPS-based ground validation points of CSAF in Rulindo