Scientific African 29 (2025) e02785

Contents lists available at ScienceDirect

Scientific African

journal homepage: www.elsevier.com/locate/sciaf

Impacts of climate-smart agroforestry practices on income and food security in two Rwandan agroecosystems

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A R T I C L E I N F O

Editor: DR B Gyampoh

Keywords:
Climate-smart agroforestry
Sustainable farming
Income
Food security
Agroecosystems
Rwanda

A B S T R A C T

Climate-smart agroforestry (CSAF) practices offer a sustainable way to improve soil health, increase farm productivity, enhance biodiversity, and boost farmers' well-being in low-income countries. This study assessed the effects of CSAF on income and food security among 381 farmer households in two contrasting Rwandan agroecosystems. Data were collected through farm-level interviews and analyzed using descriptive statistics, Pearson correlation, and multivariate latent variable regression. Results revealed that CSAF practices increased crop yield, improved food security, and diversified income sources. Livestock contributed the highest income, while tree products contributed the least. Smallholder farms (<1 ha) reported the highest profits, averaging Rwf 68,975,000 (US$ 52,175.46). Food security was higher in Bugesera (46.7 %) than in Rulindo (42.5 %). Among CSAF practices, shelterbelts and multipurpose trees significantly influenced income and profit, while silvopasture enhanced food security. Despite these findings, latent variables – factors related to farmers' attitudes towards adopting CSAF practices – have a small impact (if any) on well-being outcomes. This is important information for policymakers, as it signals the extension education needed for the farmers' understanding of the influence of CSAF adoption on improved household wellbeing. Moreover, these results suggest that CSAF practices can lead to increased income, enhanced food security, and greater resilience to climate change. This information can inform policies and guide agricultural researchers in developing and promoting more effective interventions, ultimately leading to wider adoption of CSAF.

Introduction

The climate crisis is increasingly distressing. Climate change impacts agriculture, negatively impacting the broader economy [43]. It can damage crop yields, meaning less returns from farms and less food for people [39]. Hence, mitigating and adaptive approaches are needed to reduce the decline in yields engendered by climate challenges. The effects of climate change dictate the option of sustainable farming practices such as climate-smart agroforestry (CSAF) because of its overall environmental and well-being benefits.

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https://doi.org/10.1016/j.sciaf.2025.e02785
Received 18 February 2025; Received in revised form 6 May 2025; Accepted 2 June 2025
Available online 4 June 2025

CSAF is often described as a new term labeled as an old practice of crop-tree combination for multipurpose benefits to meet the needs of the communities while addressing the effects of climate change. CSAF is a novel and smart farming practice for transforming and reorienting agricultural systems through tree integration on farms to sustain production in response to climate change. Until recently, the concept of CSAF arose from climate-smart agriculture, an approach to achieving sustainability in the agricultural sector in response to climate change [40].

CSAF is promoted for its productive and protective roles such as greater agricultural productivity, soil erosion, and runoff control, improved nutrient, and water cycling, the potential for carbon sequestration, as well as for offering socio-economic benefits [22,33,67,69]. Today, CSAF is seen as a cost-effective strategy for climate change resilience and mitigation [9], that contributes to carbon sink [24,75], enhances the provision of ecosystem services [58], and wealth creation through farm income and employment [14].

Over the last few decades, CSAF has drawn much attention from researchers and stakeholders in forestry and nature conservation science, being considered a solution to rural poverty, food insecurity, and climate change challenges [20,47] emphasized that CSAF is a viable option for overcoming these challenges while increasingly being recognized and gaining momentum. Studies have shown that CSAF has several positive impacts through the increase of productivity of croplands [60], feeds the soil with nutrients and fights soil erosion [46], protects and maintains flora, fauna, and avian diversity [70], propels economic potential for local farmers [35,59], while promoting food security [72].

Previous empirical research has focused primarily on tree-crop integration for soil control, soil fertility, biodiversity conservation, and improvement of the quality of the agroecosystems with a linear relationship to farm management. Even though several studies have documented the benefits of CSAF, relatively low adoption gaps are not fully understood [10,28,41,44,54]. Additionally, the absence of CSAF in public policy contributes to its limited recognition of tackling the climate crisis and improving rural livelihoods. This may be due to, among other reasons, a shred of less comprehensive evidence on its social, economic, and environmental impacts on the community [45].

Rwanda has pledged to restore 2 million hectares of land (almost 100 % of arable land) by 2030, mainly through CSAF, to advance agricultural productivity, derived income, and food security. Thus, this study is aligned with these land restoration programs as it seeks to understand how CSAF affects farm productivity, revenue, and food security in selected study areas.

Studies on CSAF practices given climate change and their impact on income and food security from an empirical approach are scant. Some of these issues remain unexplored and understudied, yet are extremely important and worthy of investigation in the context of recent world food price spikes [31], rising population, climate change, decreasing arable lands, and biodiversity. These studies have rarely been applied to CSAF practice adoption, specifically in Rwanda, and therefore may be inconclusive. In this study, we seek to extend inquiry by addressing the empirical gaps in prior research.

The overall objective of this study is to investigate the implications of CSAF on two dimensions of farm households' well-being: income and food security in Bugesera and Rulindo agroecosystems of Rwanda. The specific objectives of this study are as follows: first, to calculate the contribution of CSAF to farmer income and food security, and second, to determine CSAF practices that influence farmer income and food security. The leading research question of the study is: Does CSAF significantly contribute to the farmers' economic viability and food security in rural areas?

By answering this question, we can gain insights into the economic and food security viability of CSAF in the study areas and inform policies to upscale its adoption in the future.

Theoretical background

Utility theory approach

Searching for and characterizing the variables that explain farmers' decisions and choices regarding innovation involves recognizing the various spheres of farmers' activities that may impact their ultimate decisions [68]. Economists and psychologists have long examined the mechanisms of decision-making in their studies. Both random utility theory and the theory of planned behavior (TPB) are commonly used theoretical frameworks to understand farmers' decision-making processes [13]. TPB is a socio-psychological theory that effectively analyzes how farmers' intentions are formed, triggered by three key psychological constructs: attitude, subjective norm, and perceived behavioral control [3]. Since we focused on explaining how smart farming (climate resilient) approaches impact farmers' income and food security, we based our study on the random utility approach. The theory is paramount in agriculture to understand farmers' decisions when choosing an innovation. In the agricultural field, the underlying principle of expected utility theory (EUT) states, "A farmer compares the innovation with the traditional technology and decides to choose it if the expected utility from adopting the new technology exceeds the expected utility of continuing with the traditional technology" [11]. This statistical analysis approach uses a general utility theory borrowed from economics to explain individuals' behaviors in decision-making, based on the premise that people can consistently rank-order their choices in line with their preferences. Utility theory explains how decision-makers choose between two or more options by order of preference. In essence, utility theory is an "ordinal" approach, a framework for understanding consumer choices by ranking order choices under conditions of certainty [68]. Farmers' choices and decisions are usually made under uncertain conditions, stemming from various factors, including unstable weather patterns, commodity price volatility, and the unpredictable nature of agricultural production; thus, the random utility framework is a more suitable theoretical basis for analyzing farmers' decisions about adopting CSAF. The random utility framework is favored because it accounts for observable and unobservable factors influencing individual preferences, making it better suited to model choices made under uncertainty. This approach uses discrete choice modelling to predict or explain individual choices from a set of distinct alternatives, assuming that individuals choose the option that maximizes their utility, the utility often represented by a mathematical function [29].

Like the general deterministic utility function, the random utility model (RUM) framework assumes that individuals choose the alternative with the highest perceived utility by adding a probabilistic element to the choice process. The utility of an alternative, as a decision-maker perceives it, depends on attributes of the alternative and it is influenced by both observable (e.g., cost of an alternative, farmer's age) and unobservable (e.g., farmers' preferences, attitudes, experiences) attributes/factors [29]. Typically, in the utility functions, observed attributes are represented by explanatory variables (e.g., commodity price, farmer's age), while unobserved variables are denoted as random variables (e.g., preferences, unobserved information). Hence, a utility function can be expressed as [29]:

$$U_j = \beta X_j + \varepsilon_j \tag{1}$$

Where U is the utility, X_j is a vector of observed attributes of alternative j, β is a conformable vector of constant parameters, and ε is a random variable that accounts for the effects of unobserved attributes of the alternative on preferences, also known as error term, random component, or stochastic component. In the context of the current study, we assume that farmers adopt CSAF practices if the utility from adoption exceeds the utility from non-adoption [13]. The utility maximization framework, a common assumption in economics, leads to discrete-choice models used to analyze and understand farmers' behaviors in making decisions related to their farm operations [19]. In a formal model, the farmers' decision to adopt or not CSAF practices may be expressed by the binary variable Y_i. This variable takes a value of 1 if the farmer chooses to adopt CSAF on the farm and 0 if they choose not to adopt. The general notation of the possible choices can be expressed in the general formula [74]:

$$Y_i = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \text{ } if \text{ } Y_i^* = x_i\beta + \varepsilon_i \begin{Bmatrix} > \\ < \end{Bmatrix} 0 \tag{2}$$

Where β are parameters to be estimated, x_i are the explanatory variables, and ε_i is the error term with $E(\varepsilon_i) = 0$. Y_i^* denotes an unobservable latent variable, and assuming that farmer i receives a utility U_{i_j} when alternative $j(= 1 \text{ } or \text{ } 0)$ is chosen and further assuming utility-maximizing behavior, farmer i chooses an alternative $Y_i = 1$, if $U_{i_1} > U_{i_0}$.

Empirical research employing utility theory or random utility theory aims to identify how specific farm and farmer profiles influence decision-making in farm operations [13]. This involves the identification of key variables on empirical respondents referring to utility maximization, such as farming context (e.g., AEZs, climate), farm characteristics (e.g., farm size, cropping systems), farmer characteristics (e.g., age, risk-aversion), household (e.g., family size, assets), information and learning (e.g., training, extension education, farmers' attitudes and perceptions). The decision outcomes are estimated using statistical regression methods such as Logit, Probit, or Tobit models [13].

Conceptual framework

In this study, we modeled the farmers' motivation to adopt CSAF in three categories: high income, high profit, and food security. The possible correlations among the CSAF adoption for different categories of motivation (high income, high profit, and food security), caused by common unobserved factors, are included in the joint model explicitly. Two sets of variables were considered to influence the three outcome categories of CSAF adoption: exogenous and attitudinal variables. Exogenous variables include taungya systems, home garden systems, alley cropping systems, improved fallow systems, multipurpose tree farming systems, plant-crop-combination systems, shelterbelts/windbreaks systems, and silvopasture farming systems. Assuming that not all the variances in farmers' motivation in CSAF adoption are explained by the above-defined exogenous (predictor) variables, we considered an attitudinal variable – pro-CSAF attitude – that likely explains the differences in farmers' motivation to adopt CSAF. The pro-CSAF attitude was defined as the variable that describes the farmers' positive attitude to adopting CSAF and anticipated improved well-being (increased income, profit,

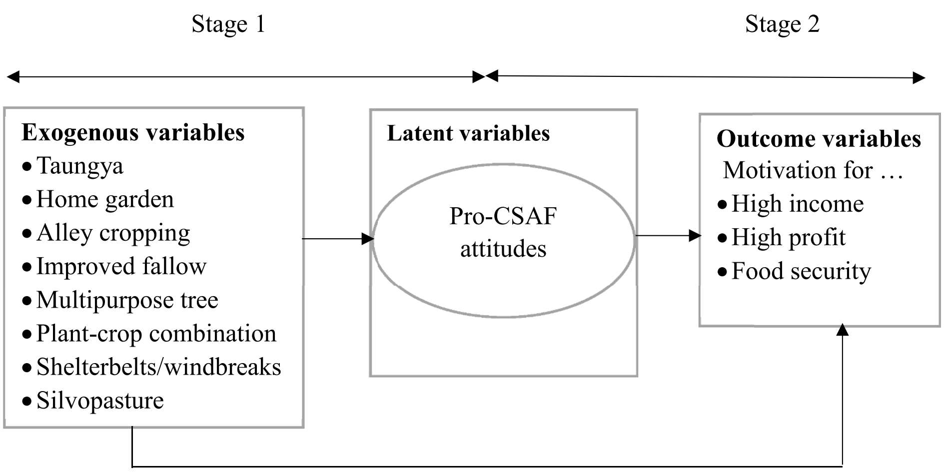

Fig. 1. Research modelling framework.

and food security). This variable is latent, which means it is a true score or underlying factor that is not directly observed and influences the observed measurements. Researchers seek to understand this unobserved variable, a trait or characteristic that is not directly measurable but is believed to affect the observed variables in the model construct. Some random measurement errors may exist because the observed score does not reflect the true score perfectly.

Fig. 1 illustrates the modeling framework used in this study. Two stages are involved in this conceptual framework. In stage one, the attitudinal latent variable – pro-CSAF attitude – is modeled using measurement and structural equation models. The measurement model focuses on the relationship between the observed parameters and the underlying, unobserved latent variables. On the other hand, the structural equation model examines the relationships between the latent variables themselves, including those influenced by exogenous (external) factors. The predicted scores of the latent variable evaluated in the measurement model are used in the next step. In this stage, a multivariate logistic model is fitted by considering two sets of predictor variables: (1) exogenous variables, which include taungya, home garden, alley cropping, improved fallow, multipurpose tree, plant-crop-combination, shelterbelts/windbreaks, and silvopasture characteristics, and (2) a latent variable related to attitude on CSAF adoption derived from the observed indicators.

It was assumed that the ability to achieve higher farm returns depends on CSAF adoption level (ability) and farmers' willingness to adopt CSAF, which, in line with the random utility theory, is determined by expected farmers' utility from undertaking additional commitments [68]. The decision by farmers, influenced by their expected utility from adopting CSAF or not, is shaped by a combination of factors such as personal characteristics (e.g., socio-demographic and attitudinal) and economic factors such as past performance and prospects (e.g., income and profits and food self-sufficiency). Researching under this assumption requires farm and farmer characteristics to understand factors influencing farmers' decisions and actions, including their attitudes, motivations, and specific agricultural practices they implement. In our analysis, we used two data sources. The first was the secondary data extracted from the Rwanda Agricultural Household Survey Report 2020 [51]. These data could deliver information on farm resources, production structure, and economic results in farmer households. These data were relied upon in determining the sample size for our study. Despite its small size (26,338 km^2), forests cover a substantial portion of the land, with 30.4 % (724,695 ha) covered by forests in Rwanda. Areas designated as forests include forest plantations (53.5 %), natural mountain rainforests (18.1 %), wooded savannah (22.3 %), and shrubs (6.1 %) (Republic of [55]). Regionally, land use follows agroecological zone patterns: in Bugesera, forests cover 17.5 % of the land (21,479 ha), while in Rulindo, forests cover 26 % (14,729 ha). Despite these figures on forest cover, statistics on trees outside forests, specifically on-farm trees - CSAF, are absent from national records [53]. This information gap in the national statistics records raises concerns about their significant role in the communities' socioeconomic livelihoods, and reporting under the United Nations Framework Convention on Climate Change (UNFCCC). For this reason, we carried out the study with the data acquired directly from a representative sample of farmers [68].

Research on modeling farmers' motivation to adopt CSAF for different benefits is plentiful in the literature. Most of the studies in line with this study are dedicated to assessing factors affecting the motivation to adopt CSAF for one or multiple categories of benefits. These studies have something in common: location features, demographics, farm characteristics, asset ownership, institutional components, knowledge, and attitude, which largely impact the motivation of farmers to adopt CSAF for one or various benefits. This study primarily contributes to existing literature in the following two ways:

(a) We distinguished and jointly modeled the motivation to adopt CSAF for three benefit categories: high income, high profit, and food security. Most previous studies didn't consider all these benefit categories or focused only on one or some of them. Increasingly, direct comparisons, as in this study, considering all three outcome variables, are rarely made in past studies.
(b) To our knowledge, no prior research has analyzed pro-CSAF attitudes as a latent (attitudinal) predictor of CSAF adoption for farmers' well-being. We agree that adopting CSAF for farmers' well-being cannot be accurately simulated by considering pro-CSAF attitudes alone. Albeit, this is the best that can be done with these cross-sectional data.

This study uses data extracted from a survey of farm households. In these data, the realization of revenue flow and profitability, food self-sufficiency among CSAF adopters, and the costs associated with running a CSAF farm business are the mixed correlated responses, with the effect of predictor variables on these responses has to be investigated simultaneously. In this respect, a method is required to integrate these variables simultaneously. In agricultural research, the analysis of variance and linear and dummy-variable regression techniques are commonly applied to predict the effects of different variables on income and food security [17]. Multivariate modeling techniques that integrate several predictor variables and simultaneously test their impact on all proxy well-being indicators are rarely used.

The remainder of this paper is organized as follows: the next section (4) presents the methodology (data used and analysis), Section 5 presents the results, Section 6 discusses the results, and the last section (Section 7) discusses the study conclusion.

Materials and methods

Study area

This study was conducted in separate agroecosystems: Bugesera in the eastern semi-arid savannah dry and hot lowland, and Rulindo in the central highlands stretching to the north of Rwanda. The edaphic and climatic conditions limit tree establishment in semi-arid zones such as Bugesera and high, steep slopes such as Rulindo.

Bugesera was selected based on its vulnerability to drought, poverty, and food insecurity. Farmers in Bugesera face long periods of drought. In past years, natural forests in this region were systematically cleared for the production and supply of charcoal to the City of

Kigali, rendering it treeless and semi-arid.

Rulindo was selected based on its steep slopes and their corollary on settlement, agricultural productivity, poverty, and food insecurity. Farmers in the Rulindo highlands farm on steep slopes with soil erosion, flood risks, landslides, and mining activities that leave open-pit mines unfilled. Study areas are illustrated in Fig. 2.

Sampling and data collection

This study employed a multi-stage stratified random sampling method to select the study zones, from which 381 farm households were sampled (Fig. 3). In the first stage, we selected the study regions. We relied on the agroecological map of Rwanda divided into four major agroecological zones, according to [30]: the eastern plains, central plateau, highlands, and area surrounding Lake Kivu. In this stage, we selected two zones (eastern plains and highlands) due to budget constraints, while considering their climatic disparities. In the second stage, two districts were selected from the two agroecological zones, one from each, considering both heterogeneity and homogeneity in certain characteristics such as biophysical and climatic conditions, cropping patterns, water resources, and irrigation systems. In the third stage, all the sectors (sub-administrative entities) were selected from each district. We then randomly selected 24 cells from each sector using stratified sampling in the fourth stage. In this context, a cell serves as the fourth-level subdivision of Rwanda's local administrative structure. One cell may comprise several villages. In the fifth stage, fifty-eight to fifty-nine villages and forty-nine to fifty villages were randomly selected from each cell in Bugesera and Rulindo, respectively, using the Rwanda village statistics [52]. In the last stage (the sixth stage), using the lists established by village leaders, we randomly selected three to four farm households from each village with no reference to farm characteristics. Using the [71] formula, a sample of 381 was obtained. 381 farmers were interviewed - 193 from Bugesera and 188 from Rulindo – from the sample drawn from the data published from the Rwanda Agricultural Household Survey Report 2020 [51]. Before the study began, the questionnaire was pre-tested to improve survey quality and prevent the omission of important information necessary for achieving our research objectives. The questionnaire covered topics involving geospatial, climatic, demographic, and farm characteristics, as well as CSAF practices. In addition, the data on the Global Positioning System (GPS) coordinates were included in the survey. Interviews with farmers took place on their farms to facilitate recording of the farm's aspects, such as geographical information data, farm size, tree counts, erosion risks, tree structure and configuration, and various other factors of interest in this study. Informal agreements were made before the start of any session with the farm household by explaining the purpose and objectives of the study. Data were collected from farmers for their production season from April to June 2023.

We interviewed household heads on their farms. Questions were asked in the local language (Kinyarwanda) and then translated into English for recording. For dependent variables, we asked farmers about the yield of CSAF in the previous season, forms of sale of woody materials from farms, consumed CSAF products share in households, sold CSAF products share on the market, the yield of food crops, consumed food crop share in households, sold food crops on the market, revenues from woody materials, revenues from food crops, revenues from livestock, off-farm income, and food security (in quantity and quality). For independent variables, we recorded information on agroecological zones, altitude, gender, age, civil status, education, household size, *ubudehe* (household poverty level), farm size, farming experience in CSAF, etc. Data were collected using a semi-structured questionnaire and personal observation in the

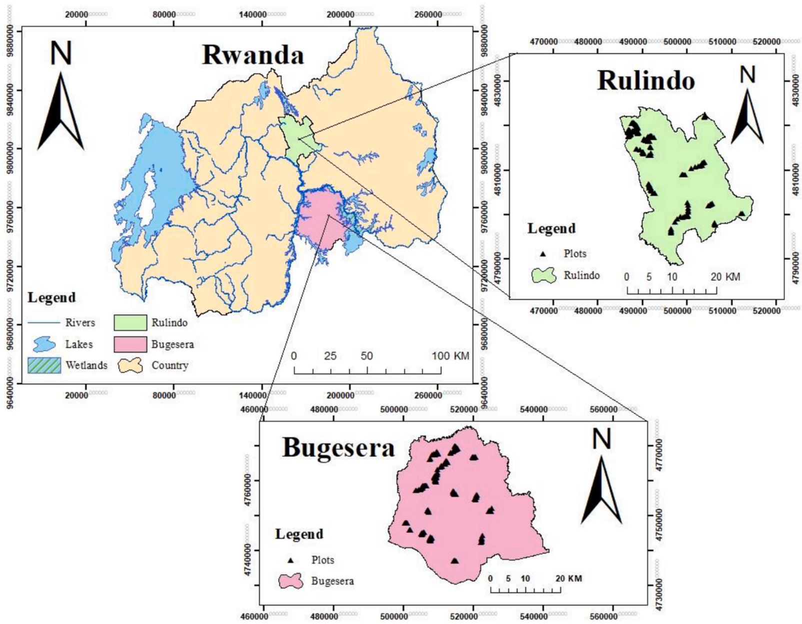

Fig. 2. Map of Rwanda with study areas (Bugesera and Rulindo) (adapted after CGIS).

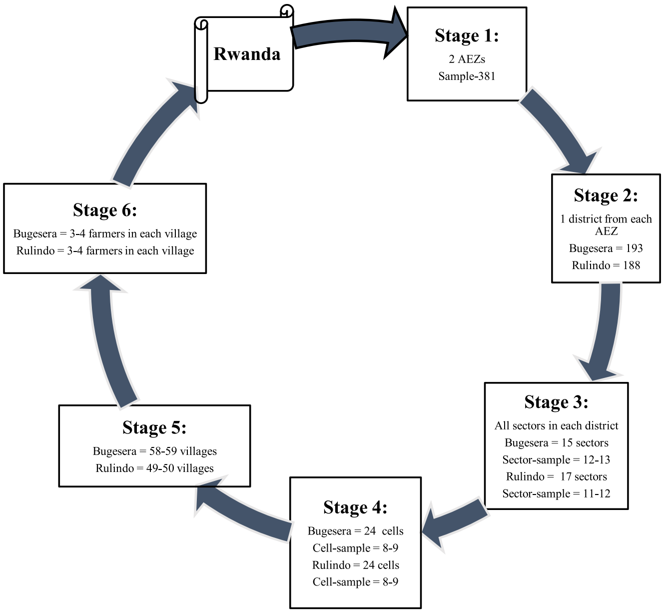

Fig. 3. Stages of sampling to select farm households in the study areas.

field. We also conducted three focus group discussions (FGDs) – two in Rulindo and one in Bugesera - with 8-12 participants. Also, interviews involved CSAF patterns and types of crops developed, information on crops, and CSAF income referring to each intercropped practice.

To gather diverse perspectives and enrich the analysis, we interviewed representatives from the local government (districts), the Albertine Rift Conservation Society (ARCOS), and the model farmers. Two interviews were conducted with local officials (districts), one interview with an ARCOS staff member, and two model farmers. These officials were contacted to acquire an overview of CSAF practices in the study areas. Their views helped to validate our findings and gain insights into the practical implementation and challenges associated with CSAF adoption.

The observation technique was also used while collecting information in the field. Secondary data were collected from various sources, notably peer-reviewed journal articles, published books, case studies, government policy documents, district development plans (DDPs), and grey literature. These data were collected to support, clarify, and interpret primary data.

Data analysis

As stated in Section 2, the modeling of motivating farmers to adopt CSAF for well-being is done in two stages. Firstly, the measurement model of the latent variable related to the farmers' attitudes towards the adoption of CSAF is defined. This formulation (measurement model) and the structural relationships between latent and exogenous variables are presented in Subsection 3.3.1. Section 3.3.2. describes the second stage of the research model, where the multivariate logistic model of three different CSAF adoption motivations is formulated.

Measurement and structural equation models of latent variables

The data used in this study were extracted from the survey on farm households conducted from April 2023 to July 2024. In these data, the realization of revenue flow and profit (continuous responses), food self-sufficiency among CSAF adopters (binary response), and the costs associated with running a CSAF farm business (continuous variable) are the mixed correlated responses and the effect of predictor variables on these responses need to be simultaneously investigated [57]. In this respect, a method is required to integrate these variables simultaneously.

In agricultural research, the analysis of variance and linear and dummy-variable regression techniques are commonly applied to predict the effects of different variables on income and food security [17]. Multivariate modeling techniques that integrate several predictor variables and simultaneously test their impact on all proxy well-being indicators are rarely used.

Structural and functional relationships in line with income and food security have been extensively researched in the literature [6, 62]. For recent literature on the impacts of climate-smart farming on income and food security modeling, see *inter alia* [73] and [20]. These studies show the relationships between the predictor and dependent variables and the underlying latent variables. The problem of investigating the influence of independent variables on response variables within a classical deterministic approach immediately follows. We can either test for the treatment effects on separate unobserved (latent) variables or attempt to combine multiple indicators into a single (latent) variable and then investigate their influence on the composite well-being variable.

Investigating the effects of explanatory variables on different indicators separately is most common in practice but problematic in several ways [17]. If many indicators are used to measure the effects of predictor variables on the proxies of well-being, separately, there is a high probability that the results will be ambiguous. The second approach, which is "substantively interesting", is multivariate modeling because it allows researchers to explore how different factors influence outcomes together, providing a more complete picture of the phenomenon being studied. Its limitation is that it is difficult to apply in practice due to some extent, the lack of appropriately and correctly collected qualitative information (e.g., farmers' attitudes towards the adoption of CSAF) for this purpose, or because of inadequate application of statistical techniques. The most commonly used methods in multivariate modeling with latent variables are based on linear structural equation modeling (SEM), which falls under the umbrella of covariance structure analysis. General structural equation models (SEMs) can be specialized to fit many classical experimental techniques, such as ANOVA, MANOVA, or ANCOVA, and also have the advantage of accounting for measurement errors and latent variables [7,8,12]. Similarly, Shimizu and Kano [76] explored the application of SEM to analyze data from experiments, providing a general expression of SEM and encompassing many classical experimental techniques. Their work particularly focused on comparing the means with MANOVA using the SEM/LV (latent variable) approach and highlighting the advantages of SEM in finding mean differences among LVs.

A measurement model defines the association between the (unobserved) latent variable and the observed predictor items. Several items were used in this study to assess the pro-CSAF attitude latent variable. The specification of the measurement model that uncovers the relationships between the latent variable and the observed items is shown in the equation below [37]:

$$\vartheta_t = \lambda_t F_l + e_l \tag{3}$$

Where $l = \{1, 2, ..., L\}$ and $t = \{1, 2, ..., T\}$ are the indices of the latent variable and observed items such that ϑ_t and F_l represent the vector of the latent variable and its respective observed items. λ_t is the vector of parameters that connect observed items ϑ_t and the latent variable F_l. ε_l represents the measurement error associated with the latent variable. 'The measurement errors are assumed to be standard normally distributed' [37].

The structural equation model specifies the relationships between latent variables (not directly observed variables) and exogenous variables (independent variables in the SEM equations) [37]. We assessed only in this study the impacts of exogenous variables on latent variables, represented by the equation [37]:

$$F_l = \beta_i X_i + r_l \tag{4}$$

where $i = \{1, 2, ..., I\}$ is the index of exogenous variables where X_i denotes the vector of exogenous variables and β_i represents their respective parameters that explain their association with the latent variable F_i. r_l is the vector residuals associated with the latent variable. This structural error term is assumed to be standard normally distributed.

Empirical estimation

To analyze farmers' decision behavior to adopt CSAF, a multivariate (instead of univariate) modeling framework is needed to account for the multiple outcomes and possible simultaneity of the decision-making process [73]. Accordingly, a multivariate logistic regression (MLR) model was used in this paper to assess the implications of CSAF practices on farmers' well-being expressed on the proxies of income, profit, and food security. In the model estimate, adopting a CSAF practice with an interest in achieving high income, profit, and food security corresponds to a binary choice (yes/no) equation, and the choices are jointly modeled while accounting for the correlation among disturbances. The multivariate specification estimates improve over the univariate specifications when the error correlations significantly differ from zero [73]. As such, the two modeling frameworks would lead to comparable results. Hence, if a farmer adopts M different CSAF practices, M equations, describing a latent dependent variable corresponding to the observed binary outcome for each CSAF practice, would need to be estimated simultaneously.

In the MLR model, the general form of the link between the linear predictor η and the expected response vector π is [27]:

$$\eta = C^t Log(L\pi) \tag{5}$$

where C is the contrast matrix and L is the marginal indicator. We illustrate the model for the bivariate case with the binary responses Y_1 and Y_2. Let $\pi = (\pi_{00}, \pi_{01}, \pi_{10}, \pi_{11})^t$, where $\pi_{kl} = \mathbb{P}(Y_1 = k, Y_2 = l)$, for $k, l \in \{0, 1\}$. Given $\eta = (0, \eta_{Y_1}, \eta_{Y_2}, \eta_{Y_1 Y_2})^t$, the link functions are given by $\eta_{Y_1} = \log\frac{\pi_{1+}}{1-\pi_{1+}}$, $\eta_{Y_2} = \log\frac{\pi_{+1}}{1-\pi_{+1}}$, $\eta_{Y_1 Y_2} = \log\frac{\pi_{00}\pi_{11}}{\pi_{01}\pi_{10}}$ (6) where the plus subscript denotes summation over the index, e.g. $\pi_{1+} = \pi_{10} + \pi_{11}$. The regression equations are given by

$$\eta_{Y_1} = \beta^t_{Y_1} x_{Y_1},\ \eta_{Y_2} = \beta^t_{Y_2} x_{Y_2},\ \eta_{Y_1 Y_2} = \beta^t_{Y_1 Y_2} x_{Y_1 Y_2} \tag{7}$$

This marginal model implies univariate logistic models for Y_1 and Y_2 marginally. The odds ratio is used to model the dependence between Y_1 and Y_2. The contrast matrix and the marginal indicator for this model are given by

$$C^t = \begin{pmatrix} 1\,0\,0\,0\,0\,0\,0\,0\,0 \\ 0\ -1\,1\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0-1\,1\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,1\ -1-1\,1 \end{pmatrix} \text{ and } L^t = \begin{pmatrix} 1\,1\,0\,1\,0\,1\,0\,0\,0 \\ 1\,1\,0\,0\,1\,0\,1\,0\,0 \\ 1\,0\,1\,1\,0\,0\,0\,1\,0 \\ 1\,0\,1\,0\,1\,0\,0\,0\,1 \end{pmatrix}$$

The 1st element of η represents the null contrast $\log(\pi_{++}) = 0$. For an observation i, the regression is given by $\eta_i = X_i\beta$, where $\beta =$

$\left(\beta^t_{Y_1}, \beta^t_{Y_2}, \beta^t_{Y_1Y_2}\right)^t$, and $X_i = \begin{pmatrix} 0 & 0 & 0 \\ x^t_{Y_1} & 0 & 0 \\ 0 & x^t_{Y_2} & 0 \\ 0 & 0 & x^t_{Y_1Y_2} \end{pmatrix}$.

Given a randomized response (RR) design, the link between the linear predictor and the expected response vector is [65]:

$$\eta = C^t \log(L\pi) = C^t \log\left(LP^{-1}\pi^*\right) \tag{8}$$

Definition of variables

The response variables in the multivariate latent variable regression (MLVR) model include three dummy variables corresponding to income, profit, and food security, respectively (Table 1). Exogenous variables comprise CSAF practices such as taungya, alley cropping, home gardens, plant-crop-combinations, multipurpose trees, shelterbelts/windbreaks, and silvopasture likely to influence the income, profitability, and food security of CSAF farmers in the cross-site agroecological zones of Rwanda (Table 1).

The taungya practice, also called agrosilviculture, involves growing, along with forest tree species, annual crops during the early stages of the establishment of forest trees [50]. In the Burmese dialect, taungya means [66] "cultivation on the hills". This smart farming practice expanded from the Southern Asia region in Burma, Myanmar, and Thailand. It was practiced as tree cover restoration in shifting cultivation. The taungya farming operations last three to five years, varying based on tree cultivars, initial tree spacing, and the species' growth rate [50]. Within three to five years, crop species are not expected to compete with tree growth, and there are complementary effects between these two species (crops and trees). By the end of the last year (third or fifth) of taungya, the tree canopy is deemed to cast much shade for the normal growth of the seasonal crops [38]. At this stage, the cultivation of crops is stopped. Taungya is believed to be one of the cheapest means of establishing tree cover on the one hand and improving food security and the community's livelihoods, on the other hand [4].

A home garden is a multispecies production system practiced around homesteads. It is termed 'village forest gardens', another term referring to the same farming practice. Home gardens combine multiple tree species of economically useful plants, such as fruit trees and medicinal plants, in small landholdings in homesteads. They are believed to enhance food supply, income, profitability, and food security, and play a protective role during extreme weather.

Alley cropping combines rows of trees with seasonal fast-growing crops grown in alleys between them. It consists of planting trees in rows to create alleys within which seasonal crops are produced. Alley cropping adoption is hypothetically associated with its ability to diversify farm income and profit, and contribute to food security.

Improved fallow is a farming technique in shifting cultivation where fast-growing, often leguminous, woody species are planted during the fallow phase to restore soil fertility and provide economic benefits such as firewood or tutors for climbing crops (beans, vines, coffee). Improved fallow is considered to have differential impacts on income, profitability, and food security. Farmers who adopt improved fallow can benefit from enhanced food security and reap useful products such as timber, fuelwood, and fruits that increase income and profits. Improved fallow is hypothetically associated with its ability to increase farmers' income and profitability (because they spend less on fertilizer) and enhance food security.

Multipurpose trees refer to fruit and other trees randomly or systematically planted in cropland or pasture to provide fruit, fuelwood, fodder, stakes for climbing crops, charcoal, and timber, among other services, on farms and rangelands. They are hypothesized to positively impact farmers' well-being as they fulfill more than one human basic need.

Plant-crop combination practices consist of plantation crops (e.g., coffee, fruit crops, cocoa, and the like), fuel wood, fodder trees, and other herbaceous or shade-tolerant crops, and are one of the distinct CSAF practices. This smart farming practice is common in tropical humid lowland regions or humid and sub-humid highland landscapes [1]. The arrangement of components in plant-crop combinations [48] varies and can be (i) plantation crops intercropping with crops, (ii) mixtures of plantation crops in alternate or other regular arrangement, (iii) integrated multi-storey mixtures of plantation crops, and (iv) shade trees and plantation crops (shade

Table 1
Definition of variables included in the regression.

Variable	Description	Values
Dependent variables		
$\boldsymbol{Y}_1$	Increased income	1 = high INC; 0 = otherwise
$\boldsymbol{Y}_2$	Increased profit	1 = high π; 0 = otherwise
$\boldsymbol{Y}_3$	Enhanced food security	1 = yes; 0 = otherwise
Independent variables		
Taungya ($\boldsymbol{X}_1$)	Adopted Taungya	1 = yes; 0 = otherwise
Home garden ($\boldsymbol{X}_2$)	Adopted home garden	1 = yes; 0 = otherwise
Alley cropping ($\boldsymbol{X}_3$)	Adopted alley cropping	1 = yes; 0 = otherwise
Improved fallow ($\boldsymbol{X}_4$)	Adopted improved fallow	1 = yes; 0 = otherwise
Plant-crop combination ($\boldsymbol{X}_5$)	Adopted plant-crop combination	1 = yes; 0 = otherwise
Multipurpose trees ($\boldsymbol{X}_6$)	Adopted multipurpose trees	1 = yes; 0 = otherwise
Shelterbelts/windbreaks ($\boldsymbol{X}_7$)	Adopted shelterbelts/windbreaks	1 = yes; 0 = otherwise
Silvopasture ($\boldsymbol{X}_8$)	Adopted silvopasture	1 = yes; 0 = otherwise

trees scattered). The diversity in plant-crop combinations reduces risk. For example, if one crop fails or if prices drop for one crop, the farmer still has other crops to rely on for subsistence or cash. Also, crops may give subsistence produce and cash income, while planted trees may bear different fruits at different times of the year for subsistence and cash income. Plant-crop combination practices are hypothesized to allow farmers to optimize farm resource use and maximize yields while diversifying their income streams and food security conditions.

Shelterbelts/windbreaks refer to rows of trees around farms and fields planted and managed as part of crop or livestock operations to protect crops, animals, and soil from natural hazards, including wind, excessive rain, seawater, or floods. Shelterbelts/windbreaks are a linear planting of trees that form part of a farmland production system that includes trees planted to reduce wind speed, protect crops, and enhance biodiversity. They are likely to increase economic returns through increased farm yields. By incorporating ornamental or fruit trees into the shelterbelts/windbreaks, farmers can market secondary products and enhance revenue flows, profits, and food security.

Silvopasture is a practice that combines trees with forage and livestock production, such as grazing in existing forests; using trees to create live fences around pasture, or providing shade and erosion control. Silvopasture is most successfully practiced as a deliberate integration of trees, forages, and livestock [34] in regions with mild, moist climates suitable for commercial timber production and livestock grazing. Multidimensional products, such as forage, saw timber, logs, fuelwood, fruits, poles, and stakes, from silvopasture contribute to revenue flows while preserving long-term productivity, and contributing to food security. Therefore, it is hypothesized that the probability of adopting silvopasture would generate higher income and profits, and enhance food security.

Estimated values of parameters

Table 2 presents a list of variables extracted from the collected data, which were used in regression to estimate the final model along with their average values. The results indicate that 95 % of farmers surveyed in Bugesera and Rulindo did not practice alley cropping or silvopasture, respectively. Practices of home gardens and shelterbelts/windbreaks were predominant (18.9 %) on farms in Bugesera and Rulindo, respectively.

Indicators of latent variables

In this study, considering that farmers' attitudes towards CSAF adoption increase income and profit, and improve food security, a latent variable – pro-CSAF attitude – was treated as the predictor of high income, profit, and improved food security. Five indicators on a binary scale were used to measure the unobserved (latent) variable (farmers' attitudes). Fig. 4 illustrates the distribution of responses regarding the indicators intended to reflect unobserved (latent) variables. Above three-fifths of the sample concurred with the statement that the overall income/benefits from CSAF are more than pure agriculture and forestry (65.62 %), CSAF improves the agroecosystem's micro-climate (66.14 %), every farmer should practice CSAF (65.35 %), CSAF reduces the incidence of total crop failure (66.93 %), CSAF helps farmers to become self-reliant in timber, fuel, fruits, and fodder (64.57 %). On average, these results show a positive attitude of farmers towards CSAF practices for their anticipated well-being.

Results

CSAF farming in Bugesera and Rulindo

Fig. 5 illustrates CSAF adoption in research areas [a] crops with trees and [b] livestock with trees. [a] Crops with trees are a way to increase crop yields: diversified cropping can support farm businesses operating year-round and circumvent the peaks and troughs of seasonal demands, thus providing a source of year-round income. [b] Livestock with trees (silvopasture) promotes ecological regeneration, diversifies income, and offers resilience to climate change impacts like droughts and storms.

Table 2
List of variables and their average values.

Variable	Unit	Total	Bugesera	Rulindo
Taungya	% yes	n/a	n/a	n/a
	% no	n/a	n/a	n/a
Home garden	% yes	31.8	18.9	12.9
	% no	68.2	81.1	87.1
Alley cropping	% yes	10.0	0.5	9.4
	% no	90.0	99.5	90.6
Improved fallow	% yes	12.6	11.3	1.3
	% no	87.4	88.7	98.7
Multipurpose trees	% yes	12.3	8.9	3.4
	% no	87.7	91.1	96.6
Plant crop combination	% yes	5.8	2.9	2.9
	% no	94.2	97.1	97.1
Shelterbelts/windbreaks	% yes	24.9	6.0	18.9
	% no	75.1	94.0	81.1
Silvopasture	% yes	2.6	2.1	0.5
	% no	97.4	97.9	99.5

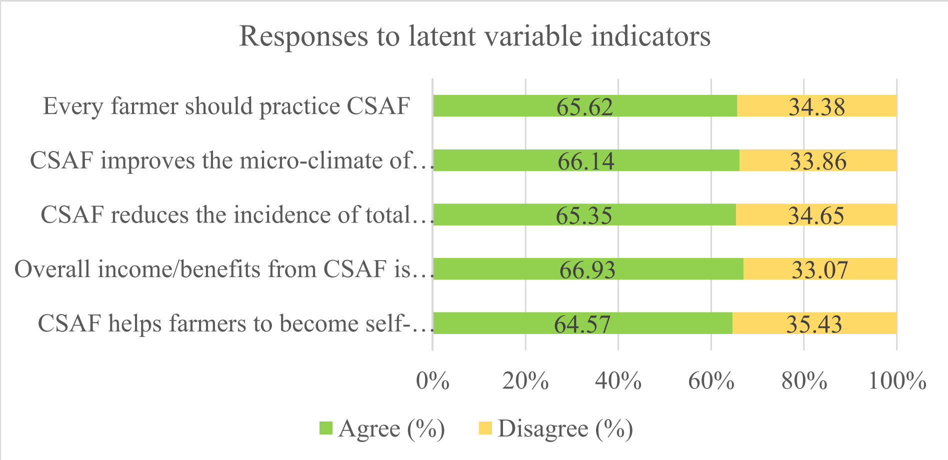

Fig. 4. Sample data for the indicators of latent variables related to farmers' attitudes towards CSAF for increased income, profit, and improved food security.

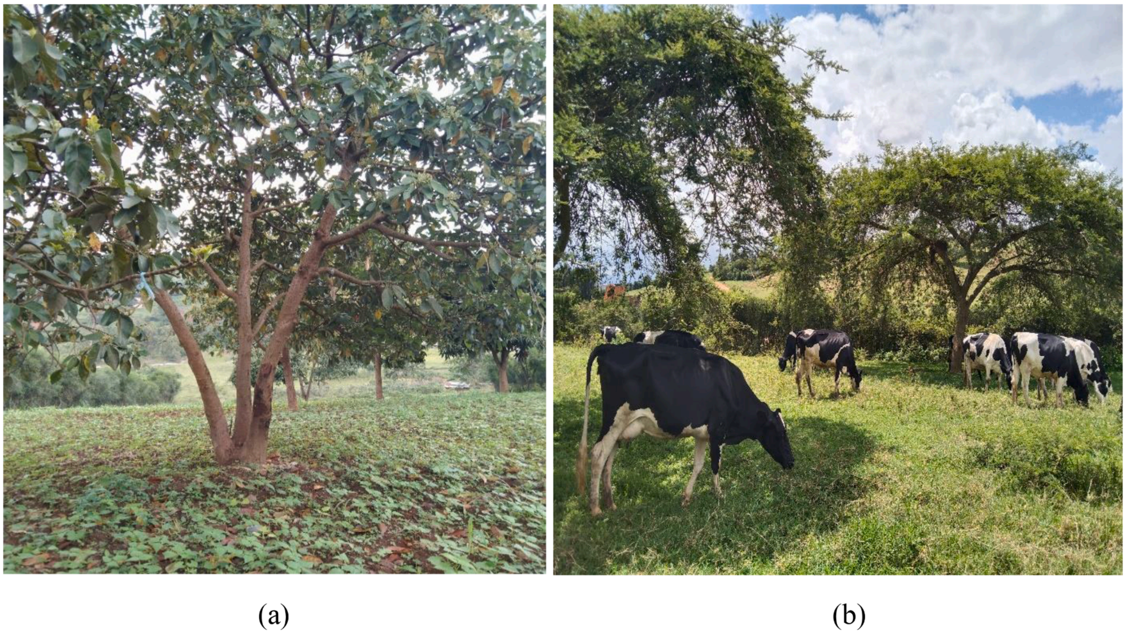

Fig. 5. CSAF farming in research locations: (a) thriving bean crop in avocado trees; (b) a well-established livestock farming in a forest plantation.

Characterization of surveyed farmer households

Table 3 shows that most respondents were male farmers (66.7 %) who managed a larger portion of the CSAF land area than female farmers, an average of 1.24 ha. The social categorization (*ubudehe*) indicates that more than ½ of respondents (55.9 %) were high-income earners and managed a larger portion of the CSAF land area than the low-income earners, with an average landholding of 1.47 ha. Farmers with more than 10 years of experience (1.8 %) managed a larger portion of CSAF land area than other CSAF experience brackets, namely an average landholding of 1.79 ha. Most of the respondents (46.2 %) farmed in low altitudes (<1500 m) and managed a larger portion of the CSAF land area than other farmers in altitude brackets, namely an average landholding of 1.55 ha. The minority of the respondents (21.3 %) were visited by agricultural extensionists and managed the largest part of the CSAF land area compared to farmers who didn't receive any visit, with an average landholding of 1.27 ha.

CSAF adoption patterns

Table 4 shows that farmers in study areas practice CSAF on farms using various techniques — home gardens, alley cropping,

Table 3
Farmer composition by demographic features.

Variable	Bugesera				Rulindo				Total			
	Freq. (n)	%	Total land holding (ha)	Average land holding (ha)	Freq. (n)	%	Total land holding (ha)	Average land holding (ha)	Freq. (n)	%	Total land holding (ha)	Average land holding (ha)
Gender												
Male	134	69.4	222.06	1.66	120	63.8	93.64	0.78	254	66.7	315.70	1.24
Female	59	30.6	63.86	1.08	68	36.2	35.32	0.52	127	33.3	99.18	0.78
Age												
<20	2	1.0	2.00	1.00	4	2.2	3.64	0.91	6	1.6	5.64	0.94
21-30	44	22.8	35.41	0.80	34	18.1	19.16	0.56	78	20.5	54.57	0.70
31-40	58	30.1	84.73	1.46	39	20.7	15.63	0.40	97	25.4	100.36	1.0
41-50	37	19.2	76.34	2.06	52	27.6	37.97	0.73	89	23.4	114.31	1.3
>50	52	26.9	87.42	1.68	59	31.4	52.56	0.89	111	29.1	139.98	1.2
Civil status												
Married	150	77.7	252.69	1.68	133	70.7	96.61	0.73	283	74.3	349.30	1.23
Not married	43	22.3	33.21	0.77	55	29.3	32.35	0.59	98	25.7	65.56	0.67
Education												
Literate	75	38.9	187.71	2.50	141	75.0	104.09	0.74	216	56.7	291.80	1.35
Illiterate	118	61.1	98.20	0.82	47	25.0	24.87	0.53	165	43.3	123.07	0.74
Household size												
1-5	149	77.2	195.58	1.31	144	76.6	78.42	0.54	293	76.9	274.00	0.93
6-10	44	22.8	90.33	2.05	44	23.4	50.53	1.12	88	23.1	140.86	1.60
>10	0	0.0	0.00	0.00	0	0.0	0.00	0.00	0	0.0	0.00	0.00
"Ubudehe"												
High income	122	63.2	232.47	1.90	91	48.4	80.35	0.88	213	55.9	312.82	1.47
Low income	71	36.8	53.44	0.75	97	51.6	48.61	0.50	168	44.1	102.05	0.61
Experience in CSAF												
0-5	140	72.5	198.93	1.42	145	77.1	86.94	0.60	285	74.8	285.87	1.00
6-10	48	24.9	75.28	1.57	41	21.8	41.19	1.00	89	23.4	116.47	1.31
>10	5	2.6	11.7	2.34	2	1.1	0.82	0.41	7	1.8	12.52	1.79
Radio												
Yes	92	47.7	194.88	2.12	95	50.5	79.82	0.84	187	49.1	274.70	1.47
No	101	52.3	91.03	0.90	93	49.5	49.14	0.53	194	50.9	140.17	0.72
Mobile phone												
Yes	152	78.8	255.45	1.68	122	64.9	93.09	0.76	274	71.9	348.54	1.27
No	41	21.2	30.46	0.74	66	35.1	35.87	0.54	107	28.1	66.33	0.62
Livestock												
0-5	178	92.2	226.11	1.27	186	98.9	121.96	0.65	364	95.5	348.07	0.95
6-10	11	5.7	33.8	3.07	2	1.1	7.00	3.50	13	3.4	40.80	3.14
>10	4	2.1	26	6.5	0	0.0	0.00	0.00	4	1.1	26.00	6.50
Altitude												
<1500	176	91.2	273.87	1.55	0	0.0	0.00	0.00	176	46.2	273.87	1.55
1501-2000	17	8.8	12.04	0.71	154	81.9	102.94	0.67	171	44.9	114.98	0.67
>2001	0	0.0	0.00	0.00	34	18.1	26.02	0.76	34	8.9	26.02	0.76
Farm-river distance												
<500m	14	7.3	40.95	2.92	38	20.2	40.62	1.07	52	13.6	81.57	1.57
>500m	179	92.7	244.96	1.37	150	79.8	88.34	0.59	329	86.4	333.30	1.01
Training												
Yes	8	4.1	28.00	3.50	47	25	48.83	1.04	55	14.4	76.83	1.39
No	185	95.9	257.91	1.39	141	75	80.13	0.57	326	85.6	338.04	1.03
Extension visit												
Yes	21	10.9	40.09	1.91	60	31.9	63.14	1.05	81	21.3	103.23	1.27
No	172	89.1	245.82	1.43	128	68.1	65.82	0.51	300	78.7	311.64	1.04

improved fallow, multipurpose trees, plantation-crop-combination, shelterbelts/windbreaks, and silvopasture. Results showed that 18.9 % of farmers adopted home garden CSAF practices in Bugesera, whereas in Rulindo, the same proportion practiced shelterbelts/windbreaks CSAF. In contrast, in Bugesera, a small fraction (0.52 %) of farmers adopted alley cropping as a CSAF practice, while in Rulindo, an equal proportion embraced silvopasture as their CSA strategy. This result suggests that alley cropping is a less prevalent CSAF practice in Bugesera, and silvopasture is similarly adopted in Rulindo, albeit in a small segment of the farming community.

Table 4
Mean distribution of CSAF practices in study areas.

	Bugesera (n = 193) Freq. (n)	Rulindo (n = 188) Freq. (n)	Total (n = 381) Freq. (n)	Mean (±SD)
Taungya	-	-	-	-
Home gardens	72	49	121	60.50(±16.26)
Alley cropping	2	36	38	19.00(±24.04)
Improved fallow	43	5	48	24.00(±26.87)
Multipurpose trees	34	13	47	23.50(±14.85)
Plantation crop combination	11	11	22	11.00(±0.00)
Shelterbelts/ Windbreaks	23	72	95	47.50(±34.65)
Silvopasture	8	2	10	5.00(±4.24)
Total	193	188	381	190.50(±3.53)

Contribution of CSAF to farm returns

Table 5 shows that the largest contribution to CSAF income and net profit came from livestock (40.45 % and 46.24 %, respectively), with an average income and profit of Rwf 297,000 (US$ 224.66) and Rwf 292,352 (US$ 221.15) per ha in the prior agricultural season. The weakest contribution in CSAF income and net profit came from tree products (2.92 % and 0.92 %, respectively), with an average income and profit of Rwf 21,460 (US$ 16.23) and Rwf 5,818 (US$ 4.40) per ha in the prior harvesting season.

Distribution of income and profit based on land area in the study areas

Fig. 6 indicates that the highest income and profit of CSAF occur in small-scale farmers' holdings of $(< 1ha)$ with an average income of Rwf 108,045,450 (US$ 81,730.32) and profit of Rwf 68,974,665 (US$ 52,175.46). Income in CSAF adopters decreases along with the area of land under cultivation from marginal farming with Rwf 108,045,450 (US$ 81,730.32) to large-scale farming with Rwf 53,252,800 (US$ 40,282.75). Besides, profit in CSAF adopters decreases from the smallholding category with Rwf 68,974,665 (US$ 52,175.46) to the medium smallholding category with Rwf 42,947,700 (US$ 32,487.52), then rises again to the large-scale landholding category with Rwf 51,249,600 (US$ 38,767.45).

Table 5
Average farmer income and profitability in CSAF adoption.

	Items	CSAF to farm returns					Total (Rwf)
		Cassava	Maize	Beans	Tree products	Livestock	
1	**Cost (Rwf)**						
	Seedlings	5,893	15,507	33,155	12,000	-	66,555
	Fertilizers	0	0	0	0	0	0
	Pest control	0	0	0	0	0	0
	Labor	2,946	7,753	16,577	3,642	4,648	35,566
	Insurance	0	0	0	0	0	0
	Total cost (Rwf)	**8,839**	**23,260**	**49,732**	**15,642**	**4,648**	**102,121**
2	**Yield ($kg.ha^{-1}$)**						
a	*Cassava ($kg.ha^{-1}$)*	*128.33*	-	-	-	-	-
	Unit price ($Rwf.kg^{-1}$)	500	-	-	-	-	-
	Cassava value ($Rwf.ha^{-1}$)	64,165	-	-	-	-	64,165
b	*Maize ($kg.ha^{-1}$)*	-	*484.75*	-	-	-	-
	Unit price ($Rwf.kg^{-1}$)	-	250	-	-	-	-
	Maize value ($Rwf.ha^{-1}$)	-	121,187	-	-	-	121,187
c	*Beans ($kg.ha^{-1}$)*	-	-	*329.31*	-	-	-
	Unit price ($Rwf.kg^{-1}$)	-	-	700	-	-	-
	Bean value ($Rwf.ha^{-1}$)	-	-	230,517	-	-	230,517
d	Tree products value ($Rwf.ha^{-1}$)	-	-	-	21,460	-	21,460
e	Livestock value ($Rwf.ha^{-1}$)	-	-	-	-	297,000	297,000
3	**Total revenue (Rwf)**	**64,165**	**121,187**	**230,517**	**21,460**	**297,000**	**734,329**
4	**Gross benefit (Rwf)**	**55,326**	**97,927**	**180,785**	**5,818**	**292,352**	**632,208**
5	**Income shared (%)**	**8.74**	**16.50**	**31.39**	**2.92**	**40.45**	**100.00**
6	**Profit shared (%)**	**8.75**	**15.49**	**28.60**	**0.92**	**46.24**	**100.00**

Note: US$1 = Rwf 1,321.975177 (exchange rate of June 21, 2024).

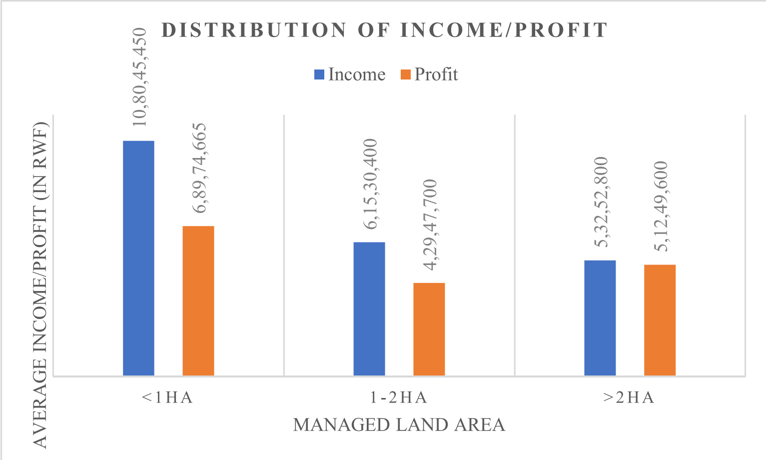

Fig. 6. Average of CSAF income/profit.

Food self-sufficiency in study areas

Food security self-sufficiency among CSAF adopters was also documented, and the results are presented in Fig. 7. The results show that, among the sampled farmers, the largest number of food-secure households was in Bugesera with 46.72 % compared to Rulindo with 42.52 %.

CSAF income, profits, and food security and their spatial patterns

As shown in Table 6, the mean income from CSAF was Rwf 2,858,547 in Bugesera (2,858,547 ± 11802045) and Rwf 5,960,819 in Rulindo (5960819 ± 26258353). The contrast was not statistically significant ($p = 0.136$). Increasingly, the mean profit from CSAF was Rwf 773,528 in Bugesera (773528 ± 21984100) and Rwf 617,617 in Rulindo (617617 ± 46920623). The contrast was not statistically significant ($p = 0.967$). On the other hand, the mean food security from CSAF was 92.2 % in Bugesera (0.922 ± 0.268) and 86.1 % in Rulindo (0.861 ± 0.346). The contrast was statistically significant ($p < 0.10$).

Variance-covariance matrix of CSAF practices with expected farmers' well-being

The variance-covariance matrix of expected farmers' well-being expressed in income, profit, and food security for each CSAF practice is given in Table 7. Results show that sole home garden practices satisfy all three expected outcomes to procure higher incomes and profits for farmers while making them food secure. Conversely, a negative covariance exists between the shelterbelts/windbreak practices and all three expected outcomes to procure higher incomes and profits for farmers while giving them food security. Other CSAF practices show positive and negative covariance with any of the three outcome indicators of well-being. Taungya was not

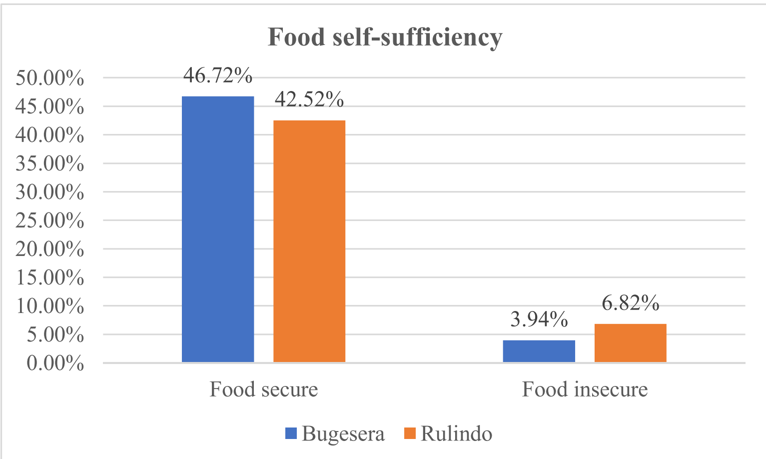

Fig. 7. Food self-sufficiency in study areas.

Table 6
Mean differences in outcome variables.

Variable	Mean (±SD)		Contrast	t	P>|t|
	Bugesera	Rulindo			
Income	2858547(±11802045)	5960819(±26258353)	-3102271	-1.49	0.136
Profit	773528 (±21984100)	617617(±46920623)	155911.6	0.04	0.967
Food security	0.922(±0.268)	0.861(±0.346)	0.060	1.91	0.0567*

* Significant at 10 %.

Table 7
The variance-covariance matrix of CSAF practices with expected farmers' well-being.

CSAF practices	Income	Profit	Food security
Taungya	-	-	-
Home garden	0.009387	0.008993	0.00795
Alley cropping	−0.001554	0.000062	0.005498
Improved fallow	−0.003896	−0.004476	0.003267
Multipurpose trees	−0.006424	0.002362	0.008047
Plant crop combination	0.007688	0.007377	−0.004296
Shelterbelts/windbreaks	−0.010464	−0.030108	−0.017834
Silvopasture	0.000145	0.00431	−0.005063

recorded in any area of study. These CSAF practices are evaluated to determine their influence on income generation, profit, and food security.

Impacts of CSAF adoption on farmers' wellbeing

Estimated measurement and structural equation models

This model involves a latent variable (pro-CSAF attitudes), and the estimation results are presented in Table 8. All the latent variables were insignificant in directly or indirectly determining farmers' well-being. Home gardens, alley cropping, improved fallow, multipurpose trees, and shelterbelts/windbreaks were negatively associated with farmers' well-being thanks to their limited adoption and upscale ($p < 0.10$, $p < 0.10$, $p < 0.05$, $p < 0.05$, $p < 0.01$) among rural communities, especially among smallholder farmers [45].

Estimated multivariate logistic model of CSAF practices on farmers' wellbeing

The methodology presented in Section 3.3.2 was implemented in R 4.3.2 © 2023 to fit the multivariate logit model of CSAF practices on farmers' well-being. Three outcome variables (income, profit, and food security) are jointly estimated with CSAF practices and latent variables, allowing the error components to correlate. The regression model includes CSAF practices presented in Table 3 and the five latent variables (pro-CSAF attitudes) (Table 9).

After checking the possible pairwise correlation between income, profit, and food security, the effect of each covariate on income, profit, and food security was estimated. Results revealed that the covariates that included multipurpose trees and shelterbelts/

Table 8
Results of measurement and structural equation models.

Variables	Coeff.	t-stat	p-value
Measurement equation model			
CSAF helps farmers to become self-reliant on fuel, fodder, timber, and fruits	−0.066	−0.335	0.738
Overall income/benefits from CSAF is more than pure agriculture and forestry	0.043	0.271	0.787
CSAF reduces the incidence of total crop failure	0.283	1.453	0.147
CSAF improves the microclimate of the area	−0.098	−0.616	0.538
Every farmer should practice CSAF	0.080	0.406	0.685
Structural equation model			
Taungya	n/a	n/a	n/a
Home garden	−0.305	−1.867	0.062*
Alley cropping	−0.357	−1.888	0.059*
Improved fallow	−0.354	−2.342	0.019**
Multipurpose tree	−0.374	−2.025	0.043**
Plant-crop-combination	−0.228	−1.074	0.283
Shelterbelts/windbreaks	−0.633	−3.730	0.000***
Silvopasture	−0.402	−1.586	0.113590
R-squared (structural equation model)	0.058		
# of observations	381		

Significance code: 0.01<***>, 0.05<**>, 0.1<*>, 'n/a' indicates not applicable.

Table 9
Parameter estimation using a multivariate logit regression model of farmers' wellbeing.

Variables	Interest in …								
	Income			Profit			Food security		
	OR	SE	P-value	OR	SE	P-value	OR	SE	P-value
Exogenous variables									
Intercept	0.386	0.862	0.270	1.532	0.702	0.543	19.223	0.860	0.000[a]
Taungya practice *(Base: Don't practice taungya)*									
Practice taungya	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Home garden practice *(Base: Don't practice home garden)*									
Practice home garden	0.390	0.889	0.290	0.253	0.715	0.054[c]	0.592	0.874	0.550
Alley cropping practice *(Base: Don't practice alley cropping)*									
Practice alley cropping	0.227	1.048	0.157	0.208	0.797	0.049[b]	1.003	1.080	0.997
Improved fallow practice *(Base: Don't practice improved fallow)*									
Practice improved fallow	0.231	0.936	0.118	0.217	0.715	0.033[b]	0.729	0.732	0.666
Multipurpose tree practice *(Base: Don't practice multipurpose tree)*									
Practice multipurpose tree	0.116	1.122	0.055[c]	0.228	0.774	0.056[c]	1.179	1.112	0.881
Plant crop combination practice *(Base: Don't practice plant crop combination)*									
Practice plantation-crop-combination	0.760	1.001	0.784	0.372	0.830	0.235	0.234	1.022	0.155
Shelterbelts/windbreaks practice *(Base: Don't practice shelterbelts/windbreaks)*									
Practice shelterbelts/windbreaks	0.148	0.969	0.049[b]	0.088	0.765	0.001[a]	0.241	0.873	0.103
Silvopasture practice *(Base: Don't practice silvopasture)*									
Practice silvopasture	0.313	1.350	0.390	0.490	0.937	0.446	0.125	1.058	0.049[b]
Latent variables									
Intercept	0.098	0.320	0.000	0.195	0.244	0.000	4.203	0.234	0.000
CSAF helps farmers …	0.948	1.059	0.960	1.190	0.726	0.810	0.560	0.894	0.518
Overall income/benefits …	0.735	0.861	0.722	0.777	0.625	0.688	2.616	0.790	0.224
CSAF reduces the incidence …	3.057	0.985	0.257	1.359	0.725	0.672	3.458	0.941	0.187
CSAF improves the micro-climate …	0.427	0.727	0.243	1.511	0.600	0.491	0.385	0.886	0.282
Every farmer should practice …	1.133	1.022	0.774	1.033	0.739	0.965	1.757	0.993	0.570
Correlations									
Intention to …									
Income	1.000	n/a	n/a						
Profit	−0.015	−0.493	0.622	1.000	n/a	n/a			
Food security	−0.032	−1.032	0.302	−0.008	−0.273	0.785	1.000	n/a	n/a

Significance code: 0.01<[a]>, 0.05<[b]>, 0.1<[c]>, 'n/a' indicates not applicable.

windbreaks were common determinants significantly associated with income and profit. Besides, home gardens, alley cropping, and improved fallow were significantly associated with profit. Notwithstanding, none of the covariates was significantly associated with the triple outcome. None of the latent variables significantly influenced income, profit, and food security. All three outcome variables showed non-significant correlations ($p = 0.622$, $p = 0.302$, $p = 0.785$).

Implications of CSAF practices on farmers' income, profit, and food security were studied using a multivariate logistic regression model (Table 8). The independent variables used in the model are taungya practice, home garden practice, alley cropping practice, improved fallow practice, multipurpose tree practice, plant-crop-combination practice, shelterbelts/windbreak practice, and silvo-pasture practice.

The odds ratio for multipurpose tree practices shows that when holding all other variables constant, farmers who practiced multipurpose tree systems were 0.116 and 0.228 times more likely to increase their income and profit than non-adopters, respectively ($p < 0.10$, $p < 0.10$). The estimated odds ratio for shelterbelts/windbreaks practices shows that when holding all other variables constant, farmers who practiced shelterbelts/windbreak systems were 0.148 and 0.088 times more likely to increase their income and profit than non-adopters, respectively ($p < 0.05$, $p < 0.01$). The odds ratio for home garden practices shows that when holding all other variables constant, farmers who practiced home garden, alley cropping, and improved fallow systems were 0.253, 0.208, and 0.217 times more likely to increase their profit than non-adopters, respectively ($p < 0.10$, $p < 0.05$, $p < 0.05$). Moreover, the odds ratio for silvopasture practices shows that when holding all other variables constant, farmers who practiced silvopasture systems increased the likelihood of becoming food secure by 0.125 times more than non-adopters ($p < 0.05$). Plantation-crop-combination practices did not significantly influence the triple outcomes (income, profit, and food security) ($p > 0.05$). The taungya variable was dropped from the model due to a lack of records in the study areas. Unexpectedly, none of the latent variables were directly or indirectly associated with farmers' well-being outcomes in the study areas.

Discussion

This study explored the impact of CSAF practices on farmers' income, profit, and food security, expressed as proxy indicators of overall well-being. Farmers' well-being indicators were recorded as binary outcomes. A multivariate latent variable regression (MLV) model was utilized to determine the implications of CSAF practices on farmers' income, profit, and food security. This model, chosen after testing numerous alternative specifications, includes exogenous variables and their interaction effects and latent variables that provide deeper insights into differences among CSAF practices in the propensity of influencing farmers' well-being.

Characterization of surveyed farmer households

The middle-aged farmer group (age 41-50) managed the largest part of the CSAF land area compared to other age groups. Overall, the middle-aged group's possession of the largest spaces of land compared to other age groups could be explained by their tendency to diversify the source of revenues via landholding and productivity. Also, they are accumulating and expanding landholdings where they could shift after retiring and still carry out lucrative activities. The younger group (age 20-40) tends to rely on off-farm jobs that procure monetary returns to meet short-term needs. Moreover, in Rwanda, farms are shrinking as farmers continue subdividing already meager holdings equally among their sons. Similar results were found in Abayi Chomman Wereda, Oromia Regional State, Ethiopia [18], where the youths are deprived of farming due to a shortage of farmlands and the small number of elders in vulnerable conditions, struggling with social problems such as health, malnutrition, and social support.

Results revealed that most respondents were male farmers (66.7 %) who managed the largest part of the CSAF land area compared to female farmers. This could be attributed to the fact that, like in many parts of the world, women are particularly disadvantaged in access to secure rights over land. These results are consistent with [23], which emphasized that women are significantly disadvantaged compared to men regarding land rights. This situation comprises the whole picture of land rights, such as ownership, management, transfer, and economic rights. Accordingly, knowing the gender of landowners is important for identifying gender gaps in farming and how gender disparities affect agricultural productivity and rural livelihoods.

Regarding the social categorization (*ubudehe*), results indicate that more than ½ of the respondents (55.9 %) were high-income earners and managed the larger portion of the CSAF land area than the low-income earners. This could be attributed to the fact that the new law (Organic Law No. 08/2005 of 14/07/2005) allows landowners to use their land as collateral in financial institutions, and there is increased investment in farming. Accordingly, high-income earners value farming as another opportunity to diversify their investments.

Farmers with more than 10 years of experience (1.8 %) managed the largest part of the CSAF land area compared to other CSAF experience brackets. This result implies that accumulated farming experiences inspire farmers to become risk-takers and to vie for larger farm sizes to increase farm productivity, feed households, and supply the market.

The minority of the respondents (21.3 %) were visited by agricultural extensionists and managed the largest part of the CSAF land area compared to farmers who didn't receive any visits from these professionals. Access to various extension services may improve awareness among smallholder farmers, and access to new ideas and information about advanced farming approaches, opportunities, and work environments [16].

CSAF adoption and correlation analysis

Results showed that farmers in study areas practice CSAF with different approaches for various purposes — home gardens, alley cropping, improved fallow, multipurpose trees, plantation-crop-combination, shelterbelts/windbreaks, and silvopasture. These sustainable farming approaches can significantly benefit farmers by boosting crop yields and improving food security [25]. These farming systems, termed "fertilizer trees", are cheaper options and positively impact crop yields and food security, while contributing to climate change mitigation [15]. The variance-covariance matrix of expected farmers' income, profit, and food security for each CSAF practice showed that sole home garden practices satisfy all three expected outcomes to procure higher incomes and profits for farmers while making them food secure. This result suggests that adopting multiple CSAF practices may increase farmers' well-being. Similar findings by [42] and [61] concluded that the amount and diversity of farmers' income had increased due to diversified CSAF practices.

Contribution of CSAF to farm returns

Livestock was the largest contributor to CSAF's income and net profit, while the weakest contribution to CSAF's income and net profit came from tree products. This result indicates that CSAF tree products still provide low income and profit to practitioners. This income from CSAF is low but is not unexpected since there are still low adoption rates of CSAF across the study areas [64]. found similar results: insignificant income gains were found among CSAF practitioner farmers in Eastern Rwanda following the newness of the project, which introduced on-farm tree planting practices in the area.

Distribution of income and profit based on land area

The highest income and profit of CSAF occurs in small-scale farmers' holdings of $(< 1ha)$ with an average income of Rwf 108,045,450 (US$ 81,730.32) and profit of Rwf 68,974,665 (US$ 52,175.46). Income in CSAF adopters decreases along with the area of land under cultivation from marginal farming with Rwf 108,045,450 (US$ 81,730.32) to large-scale farming with Rwf 53,252,800 (US$ 40,282.75). This may be attributed to large-scale farming requiring huge investments that fewer farmers can afford in rural areas. Most farmers are in the small-scale landholding category, using local knowledge and available inputs. Instead, profit in CSAF adopters decreases from the smallholding category with Rwf 68,974,665 (US$ 52,175.46) to the medium smallholding category with Rwf 42,947,700 (US$ 32,487.52), then rises again to the large-scale landholding category with Rwf 51,249,600 (US$ 38,767.45). This may be attributed to the fact that medium-smallholder farming is a transition phase to the large-scale landholder farming category. It involves a combination of various production factors, unlike in smallholder farming. Beyond the relative land availability, farmers integrate livestock such as cattle, sheep, goats, and piggery to diversify farm outputs. So, costs in this category are huge, so they reduced the profit level.

Contribution of CSAF to food self-sufficiency

The largest proportion of food-secure households among the sampled farmers was found in Bugesera, at 46.72 %, compared to Rulindo at 42.52 %. This could be attributed to the local physical (natural environment) and human characteristics (population density) disparities between the two cross-site areas. A small population density characterizes Bugesera by square km in the lowland and large-scale farmers' holdings. By contrast, a high population density characterizes Rulindo by square km in the highland and small landholdings, highly fragmented on steep hills, hindering large-scale farming to meet household basic needs.

CSAF income, profits, and food security and their spatial patterns

The mean income from CSAF was Rwf 2,858,547 in Bugesera (2,858,547 $\pm$ 11802045) and Rwf 5,960,819 in Rulindo (5960819 $\pm$ 26258353). The contrast was not statistically significant ($p = 0.136$). Increasingly, the mean profit from CSAF was Rwf 773,528 in Bugesera (773528 $\pm$ 21984100) and Rwf 617,617 in Rulindo (617617 $\pm$ 46920623). The contrast was not statistically significant ($p = 0.967$). On the other hand, the mean food security from CSAF was 92.2 % in Bugesera (0.922 $\pm$ 0.268) and 86.1 % in Rulindo (0.861 $\pm$ 0.346). The contrast was statistically significant ($p < 0.10$). These results reflect that CSAF practices offer a way to improve food security among practitioner farmers. The contrast in the study areas could be explained by the fact that Bugesera is a lowland with many opportunities to diversify farm productivity on available large landholdings. Opposingly, Rulindo is a highland with high population density, fragmented landholdings, and unproductive soils due to soil erosion and landslides, triggering food insecurity in this zone. Population migration to other provinces (especially Eastern Rwanda) for better living conditions is witnessed in this zone [49].

Implications of CSAF adoption on farmers' wellbeing

The results showed that among the eight CSAF practices investigated in this study, home gardens, alley cropping, improved fallow, multipurpose trees, shelterbelts/windbreaks, and silvopasture practices have a significant impact on CSAF adopters' income, profit, and food security.

Home garden CSAF practices were important determinants that influenced farmers' profits. This implies that home garden CSAF practices and their apparent sustainability over time contribute to farmers' household net profits from selling fruits, fuelwood, fodder, timber, and livestock products [56]. Also, [56] found that in Habro District, Western Harerge, Eastern Ethiopia, home garden products were sold cheaper under farm gate outlets (85 %), resulting in low earnings and hence low contribution from home garden practices and household well-being. Moreover, the results of this study align with the findings of comparative European studies on CSAF economics [63] in that tree product prices, such as fruits, nuts, or timber, are one of the deciding factors in profitability.

Alley-cropping CSAF practices significantly contributed to the farmers' profits in the study areas. Similar results were found [21] in their study comparing CSAF systems and conventional cabbage farming in Dschang, West Region of Cameroon, which found that alley-cropping CSAF had a higher net return than the intensive farming system. The higher net returns in the alley-cropping CSAF system than the conventional system could be explained by the fact that the costs associated with integrating pest management (IPM) are quasi-inexistent in alley-cropping CSAF systems.

Improved fallow CSAF practices significantly influenced farmers' profits in the study areas [5]. found parallel results in their study on improved fallows in western Kenya, stressing that improved fallows can be more profitable than continuous cropping and natural fallow practices. Similarly, comparable results by [2] confirmed that improved fallow CSAF practice options are more profitable than current farmers' practices. They also emphasized that in rural areas, where road infrastructure is poor and fertilizer transport costs are high, the profitability of the improved fallow option is competitive with the fertilizer farming option.

Multipurpose tree and shelterbelts/windbreaks CSAF practices influenced both income and profit. This result implies that multipurpose trees and shelterbelts/windbreaks may provide valuable cash income for rural people. Consistent with study findings in Vojvodina, Serbia, [32] argued that shelterbelts/windbreaks provide numerous socio-economic and environmental benefits when properly planned. Also, results by [26] confirmed our findings that multipurpose tree practices might improve the profitability of CSAF as they can serve various functions, notably incomes, fodder, or food (e.g., edible fruits) in rural areas.

Silvopasture CSAF practices uniquely improved farmers' food security. This could be attributed to farming livestock under trees, which may directly impact household food security by providing milk, meat, and organic manure to grow crops. Livestock raised under trees are protected from heat stress in drought-prone areas, with a high probability of providing utilities from the farm operation all year. These findings agree with [36], who qualified silvopasture practices as promising to meet global goals of promoting food security and the sustainable use of natural resources.

Conclusion

In a small-sized country with high population pressure, small-scale farming involving climate-smart agroforestry (CSAF) is a viable strategy to sustain ecosystems and a mechanism to tackle poverty in rural areas. By adopting CSAF on farms, farmers can reap direct benefits regarding food and cash income, and receive considerable indirect environmental returns.

To understand the farmers' interests in undertaking CSAF practices on their farms, we jointly modeled the interests in generating income and profit and improving food security by considering different CSAF and attitudinal variables using a combination of structural equation modeling and multivariate logistic regression frameworks. The data used in the study were collected from farmers in the Bugesera and Rulindo agroecosystems of Rwanda for April 2023 - July 2024. The estimation results showed that most CSAF practices (home gardens, alley cropping, improved fallow, multipurpose trees, shelterbelts/windbreaks, and silvopasture) impacted the triple forms of farmers' well-being, notably income, profit, and food security. Plantation-crop-combination CSAF practice was the only nonsignificant variable not associated with the triple well-being outcomes. Increasingly, none of the latent variables impacted the triple forms of farmers' well-being.

This study identified the critical interest in CSAF adoption in different well-being outcomes (income, profit, and food security). These findings could be used to understand the economic and food security viability of CSAF practices in study areas and inform policies to upscale their adoption in the future. The positive impact of most CSAF practices on different well-being outcomes in this study could attract more individuals to adopt CSAF as a path to sustainable farming, income, and food security.

Our study is more robust than previously published studies, mostly in three aspects. First, considering three well-being outcomes (income, profit, and food security) induced by CSAF practices is rarely made in past studies. Second, we selected a range of exogenous variables (home gardens, alley cropping, improved fallow, multipurpose trees, plantation-crop-combination, shelterbelts/windbreaks, and silvopasture) rarely used to predict farmers' well-being in previous studies, in addition to attitudinal variables. Exogenous variables were used to determine their impact on farmers' well-being, holding other factors constant. In addition, individual differences in the perception of well-being outcomes might exist regardless of the differences in the CSAF farming approaches, and considering stochastic attitudinal variables captures such differences somehow, as in this study. Third, unlike past studies, we quantified the impact of exogenous and latent variables on the outcome variables using odds ratios versus control variables. These results may inform policymakers on the extent of CSAF practices and tailor effective interventions for adopting and upscaling CSAF.

We identified two shortcomings in this study that could be addressed through further research. First, the study is limited, considering that none of the latent variables impacted the triple outcomes of CSAF practices. However, other attitudinal variables might potentially influence the farmers' well-being outcomes of CSAF practices. Second, the available dataset was cross-sectional and might not correctly capture farmers' characteristics and interests in farmers' well-being outcomes from adopting CSAF and their variations in a cross-site comparative study. More realistic estimates could be obtained by analyzing whether CSAF's best management practices (BMPs) directly or indirectly influence farmers' well-being. No prior research has analyzed pro-CSAF attitudes as a latent (attitudinal) predictor of CSAF adoption for farmers' well-being. We agree that adopting CSAF for farmers' well-being cannot be accurately simulated by considering pro-CSAF attitudes alone. However, this is the best that can be done with these cross-sectional data. Alternative paths of model building and different estimation methods could be considered for robust analysis and decision-making, ensuring a comprehensive understanding of the data and potential outcomes. The study used the SEM statistical technique, a type of covariance structure analysis, specialized to fit data from various experimental designs, especially those involving complex relationships and latent variables. Further studies should leverage the capabilities of multivariate Gaussian modeling to address complex problems involving multiple correlated variables, as these methods offer powerful tools for regression, classification, and uncertainty quantification.

Ethical statements

This study was reviewed and approved by Professor Maulid W. Mwatawala, the Vice-Chancellor of Sokoine University of Agriculture, on behalf of the Tanzania Commission of Science and Technology [approval number: SUA/ADM/R.1/8/851, dated 16th March 2022]. Before starting fieldwork, we received approvals from district mayors, and informed consent was obtained from all participants in the study. All information was confidential and used for research purposes only. Anonymity was maintained using coded identifiers during analysis to guarantee all personal information would stay private.

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. **Kenneth L. Leonard:** Writing – review and editing, Validation, Project administration, Supervision. All authors have read and agreed to the published version of the manuscript.

Data availability

Data will be made available on request.

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.

Acknowledgments

Donatien Ntawuruhunga acknowledges Partnership for Skills in Applied Sciences, Engineering and Technology (PASET) through the Regional Scholarship and Innovation Fund (RSIF) for financial support to his PhD program at Sokoine University of Agriculture in Tanzania. PASET had no role in the study design, data collection and analysis, the decision to publish, or the preparation of the manuscript. The findings and conclusions of this study are those of the authors and do not necessarily represent the views of PASET.

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