World Development 173 (2024) 106405

Contents lists available at ScienceDirect

World Development

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

Agricultural production and food security implications of Covid-19 disruption on small-scale farmer households: Lessons from Kenya

James Mutegi [a,*], Ivan Adolwa [a], Abed Kiwia [b], Samuel Njoroge [a], Angela Gitonga [a], Joses Muthamia [a], Eileen Nchanji [c], Franklin Mairura [d], Kaushik Majumdar [e], Shamie Zingore [e], Thomas Oberthur [e], Mercy Kiremu [f], Monica Kansiime [g]

[a] African Plant Nutrition Institute, c/o IFDC, ICIPE Duduville Complex, Off Kasarani Road, P.O. Box 30772, Nairobi, Kenya
[b] Alliance for a Green Revolution in Africa (AGRA), West End Towers, 4th Floor, Kanjata Road, off Muthangari Drive, Off Waiyaki Way. P.O. Box 66773, Nairobi, Kenya
[c] International Center of Tropical Agriculture (CIAT), c/o ICIPE Duduville Complex, Off Kasarani Road, P.O. Box 823-00621, Nairobi, Kenya
[d] Department of Water and Agricultural Resource Management, School of Agriculture, University of Embu, P.O. BOX, 6-60100, Embu, Kenya
[e] African Plant Nutrition Institute (APNI), Lot 660 Hay Moulay Rachid, 43150 Benguérir, Morocco
[f] Te Whatu Ora Health New Zealand Waikato, Pembroke Street, Private Bag 3200, Hamilton 3240, New Zealand
[g] Centre for Agriculture and Bioscience International (CABI-Kenya), Canary Bird, 673 Limuru Road, Muthaiga, P.O. Box 633-00621, Nairobi, Kenya

ARTICLE INFO

Keywords:
Covid-19
Smallholder farmers
Farm typology
Vulnerability
Food security

ABSTRACT

A range of studies have highlighted the negative impacts of Covid-19 disruptions on incomes, food and nutrition security among rural agricultural communities in developing countries. However, knowledge of how such disruptions affect different categories of small-scale farmers in Sub-Sahara Africa is lacking. We used a mixed-method approach to collect data and determine the impacts of Covid-19 on farm input use, agricultural production, access to agricultural information services, and food security among small-scale farmers from Makueni, Nakuru, Siaya, Kakamega, and Bungoma counties in Kenya. A FAO-adapted farm household typology was developed with farm type 3 (wealthiest), farm type 2 (resource-constrained) and farm type 1 (most resource-constrained) farmer categories. Covid-19 related disruptions led to decreased use of improved seeds, fertilizers and access to extension services across the three farmer categories. Farm type 3 farmers recorded the lowest Covid-19 disruption driven reduction in the use of improved seeds and fertilizers, compared to farm type 2 and 1. Contrariwise, farmers increased manure application rates by 33%, with manure-associated expenditure rising by 129% across all counties. Average crop incomes decreased in three of the five study counties, i.e., Kakamega, Nakuru and Siaya, with the strongest decrease observed among farmers in type 1 and 2 households. A lower proportion of type 3 farmers were worried about not having enough food (43% of farmers) compared to type 1 (70%) and type 2 farmers (71%) across Counties. The sale of household assets and livestock commonly used as measures for household wealth implies that such disruptions leave vulnerable farmers poorer and hungrier. The findings propose that policy strategies are needed to recognize heterogenous Covid-19 effects and provide targeted interventions for household types most vulnerable to future disruptions of the agrifood system.

1. Introduction

The Covid-19 pandemic was first reported in December 2019 in Wuhan, China (Singhal, 2020, Page et al, 2021). It spread rapidly across the globe, necessitating the World Health Organization (WHO) to declare it a global pandemic in March 2020 (Cucinotta and Vanelli, 2020). As of April 2022, there were over 490 million documented Covid-19 cases with almost 6.2 million associated deaths globally (Worldometer, 2022). The Covid-19 pandemic has since become an unprecedented public health crisis that has led to multiple and complex global and regional socio-economic crisis. The first case of Covid-19 in Kenya was reported on March 13th, 2020, and the disease continued to spread rapidly in the country during 2020 and 2021, with the peak prevalence being observed between the 4th quarter of 2020 and the 2nd quarter of 2021 (MOH, 2021). Consistent with WHO guidelines, the Kenyan government instituted several containment measures, including

* Corresponding author.
E-mail address: j.mutegi@apni.net (J. Mutegi).

https://doi.org/10.1016/j.worlddev.2023.106405
Accepted 21 September 2023
Available online 12 October 2023
0305-750X/

restricted movements, border closures, social distancing, quarantines, and closure of social gathering places, including learning, hospitality and religious institutions to flatten the disease spread curve.

Studies indicate that Covid-19 led to major disruptions in several economic sectors of the Sub-Sahara Africa (SSA) region, including projected losses of 25 million jobs and food system disruptions (Demeke et al., 2020; Nchanji et al., 2021; Nchanji and Lutomia 2021a; Nchanji and Lutomia, 2021b). Consequently, there are increasing concerns regarding the impacts of Covid-19 on the achievement of SDGs 1 (eliminating poverty) and 2 (eliminating hunger), as the pandemic has threatened to reverse years of progress towards ending hunger and poverty (Nchanji and Lutomia, 2021a; Arndt et al. 2020; Griffith et al., 2020).

Rapid assessments were conducted relating to the effects of Covid-19 on agricultural performance and food security, but in-depth analyses of causal-effects and implications within diverse farming socio-economic groups are lacking. Most of the Covid-19 impact studies were conducted through telephone interviews (e.g. Agamile, 2022; Kansiime et al., 2021) during the earlier phases of Covid-19, when the broader pandemic impacts were yet to be experienced and understood. This study utilizes field observations covering a longer Covid-19 history as it was initiated 17 months (three Kenyan cropping seasons) after the Covid-19 outbreak. An evidence-based assessment of how Covid-19 pandemic effects vary between different households and socio-economic segments is lacking in the contemporary Covid-19 literature. Adhikari et al (2021) studied the effects of Covid-19 on food security dimensions in Nepal, while highlighting the effects of Covid-19 on poor farmers without systematically exploring effects among different farm socio-economic groups. Samad et al (2022) investigated Covid-19 effects on fishing communities in Bangladesh, including disruptions on the fish value chain, while Ogada et al. (2021) explored Covid-19 effects on African Leafy Vegetables value chains. Kansiime et al (2021) observed that the effects of pandemic disruptions differ with individual households.

This research gap needs to be addressed using approaches that clarify the role of household welfare in coping with such disruptions. It could be expected that owing to limitations of financial and social safety nets, poorer households are likely to be more vulnerable than wealthier households (Bloem and Farris, 2022), but the extent of impact, distribution, and coping strategies are not clear. Our study uses a systematic and multi-dimensional approach to define socio-economic farm types, which is a unique approach relative to approaches employed by the earlier Covid-19 impact studies that tended to aggregate all the smallholder farmers together. In addition, while earlier Covid-19 agricultural and food security disruption studies are more prevalent in other regions e.g. Asia, (Adhikari et al., 2021, Samad et al., 2022), there is a paucity of data on the quantification of the impact of Covid-19 disruption in the small-scale SSA agricultural sector at the household level. The identification of farm heterogeneity using a farm typology is necessary for targeting development programs aimed at mitigating the impact of disruptions like Covid-19 pandemic on smallholder farm households.

Results and trends based on in-depth analysis are crucial for future response and mitigation, at a time when agriculture and development initiatives are threatened by multiple potential disruptors. These potential disruptors include but are not limited to zoonotic pandemics like the Monkeypox and Marburg viruses, global climate change, global and regional economic crises, and geopolitical crises such as the ongoing Ukraine-Russia conflict. Against this background, we conducted a study to evaluate the impact of Covid-19 on small-scale farmers' agricultural production, food security and livelihoods in Kenya. The specific objective was to determine the impacts of Covid-19 on the level of use and non-use of farm inputs, adaptations, and food security in small-scale households of varying wealth categories (typologies) in Kenya. The study hypothesized that there were differences in the effects of Covid-19 on household welfare outcomes among different wealth categories of smallholder farm types in Kenya, specifically regarding:

i) Food security outcomes
ii) Agricultural input access and utilization
iii) Access to knowledge and extension services
iv) Adaptation techniques to address disruptional effects on food security
v) Development of adaptation techniques to address disruptive effects on food and nutrition security

2. Materials and methods

2.1. Study area context

The study was carried out in the counties of Makueni in lower Eastern Kenya, Nakuru in the central Rift, Siaya in the lake basin region (Nyanza), and Kakamega and Bungoma in Western Kenya (Fig. 1). The five counties are characterized by culturally, politically, and socially diverse communities (Muinde et al., 2021). Makueni County is one of Kenya's arid and semi-arid counties, receiving between 500 and 1,500 mm of rainfall in the low-moorland areas and the sub-humid hilltops, respectively. Seasonal rainfall is highly variable and erratic, leading to frequent periods of water scarcity, crop failure and low resilience to climate change. The most commonly grown crops in Makueni are drought-resistant crops including legumes (cowpeas, pigeon peas, green grams) and cereals (short-duration drought-tolerant maize varieties). Nakuru County is an agro-ecologically, socio-economically diverse county stretching from low agricultural potential to the very highly agricultural productive Kenya bread-basket areas.

The rainfall pattern is bimodal, ranging from 800 to 1400 mm annually, depending on altitude (CGON, 2018). The main food crops produced in Nakuru include cereals (maize, wheat), legumes (common beans), and roots and tubers (Irish potatoes). Fruits and vegetables (such as tomatoes, peas, carrots, onions, french beans, citrus, peaches, apples, cabbages, strawberries, asparagus, and leeks) are also commonly cultivated. Kakamega and Bungoma counties are located in western Kenya. The annual rainfall pattern ranges from 400 to 1800 mm in Bungoma County (CGOB, 2018) and 1280–2214 mm in Kakamega County (CGOK, 2018). Their main food crops include cereals (maize, sorghum, finger millet and rice), pulses (common beans and grams), and roots/tubers (cassava, sweet and arrowroots). Siaya County is more arid in the southern part and wetter towards the higher altitudes in the northern part, including Gem and Ugenya Sub-Counties. Major food crops are cereals (maize, millet, rice), sugarcane, vegetables (kales, African leafy vegetables), roots and tubers (sweet potatoes, cassava) and legumes (groundnuts and common beans) (CGOS, 2018). The major biophysical, climatic, and demographic characteristics of the 5 Counties are presented in Table 1. As of August 2021, when we carried out this study, the Covid-19 prevalence rate was highest in Nakuru County (10.9 %), followed by Makueni (9.1 %), Siaya (6.2 %), Bungoma (5.6 %), and least in Kakamega County (5.2 %). In all the survey counties, the rainfall is bimodal, with the long rains occurring in March –May, while the short rains occur during October – December each year (Jaetzold and Schmidt, 2007a; Jaetzold et al., 2007b; Jaetzold et al., 2007c).

2.2. Sampling design and sample size

A multi-stage sampling method was adopted to collect data from the five target Counties. This method was used to explore the socio-economic and biophysical diversity of farm households. This approach improves sampling accuracy by optimizing sub-sample selection while preserving key attributes of the sample population (He et al., 2015). First, Counties were purposively identified, followed by a random selection of the sub-counties within identified counties. The skip interval method was used for household sampling at the ward level where every two households in Makueni County were skipped, and every three households in the four other Counties (Dossa et al., 2011. The low population density necessitated skipping fewer households in Makueni

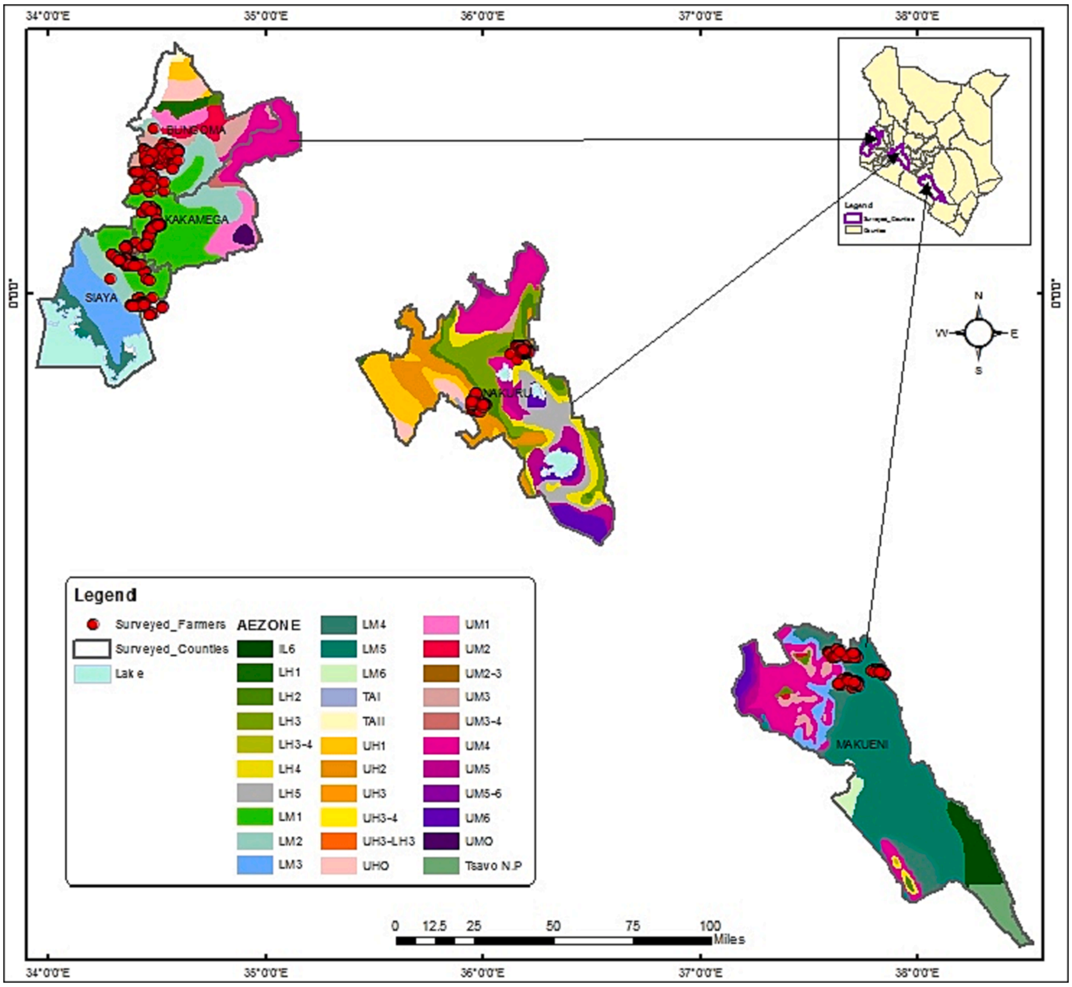

Fig. 1. Location of the study areas on the Kenya map.

Table 1
Sample distribution of farms and general characteristics of survey Counties.

Characteristic	Makueni	Nakuru	Kakamega	Siaya	Bungoma	Total
Household sample size	144	143	134	138	144	703
Household inhabitants	380	363	365	322	410	1,840
Sampled Sub-Counties	Makueni, Mbooni	Bahati, Njoro	Matungu, Mumias East, Mumias West	Gem, Ugunja	Bumula, Kabuchai	–
Census population (KNBS, 2019)	987,653	2,162,202	1,867,579	993,183	1,670,570	7,681,187
Population density (persons /km ^{2} (KNBS, 2019)	121	290	515	393	552	–
Poverty level (%) *	34.8 %	29.1 %	49.2 %	27.3 %	34.2 %	–
Annual rainfall (mm)*	250–900	800–1400	1280—2214	800–2000	400–1800	–

*Poverty level and annual rainfall distribution data were derived from respective County Integrated Development Plans (2018–2022).

(Table 1). The sampled household population included 703 households with an estimated 1,840 household members (Table 1).

2.3. Data collection and management

Household level data was collected using a digitized questionnaire (SurveyCTO Collect ™) after expert consultation and a detailed review of relevant literature to identify key research gaps of Covid-19 impacts on small-scale agriculture, household food security and welfare in the SSA region. A one-day training of enumerators was conducted, followed by pretesting of the questionnaire in each of the 5 Counties to evaluate its effectiveness in capturing the intended study parameters. The training themes for the survey enumerators included the operation of the mobile application tool, the appropriate translation of questions, data types and quality, research ethics, probing skills, triangulation skills, and basic arithmetic skills (needed to convert local units into standard units, including distances, land areas, and masses (farm inputs, farm outputs, and food intake). Survey enumerators were sourced from the specific localities where they were deployed to allow for effective data collection, given their rapport and familiarity with local dialects and farming systems. The outputs of the pretest data were used to modify and develop the final version of the survey questionnaire.

The survey exercise was carried out on various dates between 1st and 31st August 2021. The questionnaire included similar questions that compared Covid-19 outcomes during the Covid phase (long and short rain season, 2020) and the pre-Covid phase (long and short rain season, 2019). The types of data collected included crop production and input use (including fertilizer, manure and improved seeds), sources of agricultural information, house-hold food sufficiency, and food consumption data (quantity and frequency) that was used to calculate the food consumption score and daily calorific intake values. The follow-up data cleaning process included checking for omissions, typographic errors, standardization of measurement units and cleaning of outliers. The livestock count data was transformed into TLU (Tropical Livestock Units) using conversion factors proposed by Peregrine et al. (2020), Ahmed and Mesfin (2017) and Jahnke and Jahnke (1982). It included, bull/oxen (1.0), calf (0.25), poultry (0.013), cow (1.0), donkey (0.7), goat and sheep (0.1), heifer (0.75), pig (0.3), and rabbit (0.02). The TLU values were then summed to obtain each farm's aggregate TLU. The TLU value provides an approach for producing an aggregate livestock quantification, which indicates a measure of livestock intensity, stocking rates and wealth within farms (Njuki et al., 2011). For economic data, all values were converted to US$ equivalents using the US$ to Kenya shilling exchange rate of Ksh109.4. This was the average exchange rate during the survey period (CBK, 2021).

2.4. Crop and food classification scheme

The survey revealed a high diversity of cultivated crop enterprises in the 5 Counties (>50 different crops). For purposes of analysis, the crops were categorized and reported using FAO crop classification guidelines shown in Table 2 (FAO, 2015). The crops planted by farmers in all survey sites represented 9 FAO (Food and Agriculture Organization) classes, including cereals, fodder, fruits, legumes, stimulants, sugarcane, tobacco, tuber crops and vegetables. In addition, the various major foods consumed by farmers were classified as cereals, eggs, fish, fruits, legumes, nuts and seeds, meat, milk and milk products, oil, roots and tubers, sugar, and vegetables (Table 2). The calorific values of 100 g food servings of different foods consumed by the households are presented in parenthesis (Table 2).

Table 2
Crop production and food consumption classification scheme adopted in the context of the survey.

Crop classification	
Cereals	Maize, rice, sorghum, wheat, millet
Fodder	Napier, bracharia grass
Fruits	Avocado, banana, lemon, mangoes, oranges, passion fruit, pawpaws, guava, watermelon
Legumes	Common beans, cowpeas, french beans, green grams, green gram, ground nut, bambara bean, green peas, pigeon peas, Soyabeans
Stimulants	Capsicum, coffee
Sugarcane	Sugarcane
Tobacco	Tobacco
Tubers	Arrowroots, cassava, Irish potatoes, sweet potatoes, Yams
Vegetables	Amaranthus, cabbage, carrots, coriander Cucumber, indigenous vegetables, onions, pumpkin, spinach, kales, tomatoes, tree tomato
Food classification and calorific values (100 g servings)	
Cereals	Maize and maize products (86), millet (378), rice (130), sorghum (339), wheat and wheat products (364)
Eggs	Eggs (155)
Fish	Fish (129)
Fruits	Banana (89), various fruits (65)
Legumes, nuts, and seeds	Common beans (333), cow peas (116), green grams/ mungbean (105), green pea (84), groundnuts (318), macadamia (716), pigeon peas (343), soya beans (416)
Meat	Beef (250), chicken (239), pork (242)
Milk and milk products	Milk and milk products (42)
Oil	Cooking oil (884)
Roots and tubers	Arrow roots (65), cassava (159), Irish potatoes (77), sweet potatoes (77), yams (118)
Sugar	Sugar (387)
Vegetables	Lentils (116), pumpkin (26), indigenous vegetables (65)

Classification *based on* FAO, 2015.

2.5. Household food security measures

Different measures were used to assess household food security, including the Food Consumption Score (FCS) and Food Insecurity Experience Scale (FIES). Nine different questions, captured as binary data (presence or absence of the conditions) were used to assess different household perceptions of food security during the Covid-19 phase. The FCS index was developed by the World Food Programme (WFP) and validated by Wiesmann et al. (2009) as a method for establishing the prevalence of food insecurity (WFP, 2005, 2007). The FCS aggregates household-level data based on the diversity and frequency of food groups consumed, after which it is weighted according to the relative nutritional value of the consumed food groups. Food groups containing nutritionally dense foods, such as animal products, were allocated greater weights than those containing less nutritionally dense foods, such as tubers. Food items were first classified into food groups to calculate the farm-level FCS. The consumption frequencies of food items in each food group were then summed up and multiplied by their weights, followed by a summing of weighted scores to obtain the FCS. The household's food consumption status was subsequently classified based on the following thresholds: 0–21.4: Poor consumption; 21.5–35: Borderline consumption; >35: Acceptable consumption (Wiesmann et al., 2009). The food class weights that were used are as follows: Main staples (2), pulses/legumes (3), vegetables (1), fruit (1), meat/fish (4), milk (4), sugar (0.5), and oil (0.5) (Wiesmann et al., 2009).

The FIES (FAO, 2016), is an experience-based measure of access to food, and it has been validated for cross-cultural use. It employs questions related to anxiety and uncertainty about access to food. The key questions employed by this study for FIES included, whether farmers were worried about not having enough food, whether farmers did not consume preferred food due to lack of resources, whether farmers consumed a limited variety of foods due to lack of resources, whether farmers consumed unpreferred foods due to lack of resources, whether farmers consumed smaller meals due to lack of food, whether farmers consumed fewer meals in a day due to food unavailability, whether there was no food in the household due to lack of resources to get food, whether any household member slept hungry due to lack of food, and whether farmers spent a whole day and night without taking any meal due to lack of food.

2.6. Fertilizer N (nitrogen) application rate

Inorganic fertilizer input application data was captured during the survey as kilograms (kgs) applications in different crop enterprises and field application areas (acres). The fertilizer N application intensity (kg N/ha) was calculated for different fertilizer types that were used by farmers as enumerated from farm fields using the nitrogen contents (%) obtained from fertilizer manufacturers' databases as follows: UREA (46 %), YaraBela Extran (33.5 %), CAN (27 %), Mavuno-Top Dress (26 %), NPK –23:23:0 (23 %), Yara Mila Cereal (23 %), DAP (18 %), NPK17:17:17 (17 %), YaraMila Power (13 %), Folia Feeds (12 %), Mavuno Planting (10 %), and NPK 10:26:10 (10 %). The percentages were multiplied by the input kilogram rates for each crop, divided by the crop areas (ha) and reported in kilograms of nitrogen per hectare (kg N/ha).

2.7. Farm typology and vulnerability assessment

The diversity and heterogeneity of farm households was explored using multivariate methods, including Principal Component Analysis (PCA) and Cluster Analysis. The farm typology classification adapted structural typological approaches (Alvarez et al., 2014; Tittonell, 2014), while variable selection principles were guided by FAO (2018), Alvarez et al. (2014), Tittonell (2014) and Tittonell, Vanlauwe, Leffelaar, Rowe, & Giller (2005). Structural farm typologies are mainly based on variables that describe farm resource endowment (Blazy, Ozier-Lafontaine, Doré, Thomas, & Wery, 2009; Tittonell, 2014). The development of the farm typology was based on the objectives of the research as a first step, followed by the selection of key variables for characterizing the farming systems. The variables that were selected for the farm typology included numeric type measurements describing household social and wealth characteristics during the 2019 baseline pre-Covid-19 phase (Table 3). Off-farm income was obtained by summing all off-farm incomes at the farm level, while crop income and land area were obtained at the field level by summing total income from various crop types that households in the target Counties cultivated. The total annual household income was obtained by summing off-farm income, livestock income and crop income, while household margins were obtained by subtracting the total household incomes from annual household expenditures. The first stage in the typology development reduced the dimensionality of the data and identified primary patterns and variability using PCA in R with the package *ade4* (Dray and Dufour, 2007).

The choice and selection of relevant principal components (PCs) was performed by a scree plot, in the process retaining factors with eigen values > 1. During the second stage, hierarchical clustering analysis (HCA) was implemented on the reduced principal components using the *ade4* R package. Cluster memberships were determined in the last step, using Ward's criteria (Ward, 1963), generating three farm types (hereafter farm type 1, farm type 2 and farm type 3). The resultant cluster membership was saved as a variable and used in multi-faceted analyses (Table 3). The farm vulnerability was assessed using seven binary input variables that described the extent of the farm-level vulnerability. This included the presence of disabled members, possession of a health insurance cover, presence of a regular source of income, presence of elderly household heads (over 70 years), whether household head has a chronic health condition, whether the household owns land, and whether household land is in a politically volatile area. The variables were converted into binary formats, accounting for the negativity of the variables, summed, and expressed as a percentage of 7 variables. The vulnerability index was subjected to ANOVA, using the farm type variable. The farm type variable was used to compare different farm variables using one-way ANOVAs, after which means were separated using the LSD test at $p < 0.05$ to determine differences in agricultural production, farm input use and food consumption parameters. The *agricolae* R package, using the *aov* procedure for ANOVA followed by the *LSD test* procedure for post-hoc tests were implemented.

Table 3
Structural variables for farm typology description and vulnerability assessment during 2019, pre-Covid-19 phase.

Structural farm typology variables	**Measurement type (units)**
Age of household head	Numeric (years)
Years of education of head	Numeric (years)
Years of farming experience as head	Numeric (years)
Total cropped area	Numeric (ha)
Annual off-farm income	Numeric (USD $hh^{-1}yr^{-1}$)
Tropical Livestock Unit	Numeric (Unitless-dimensionless number)
Total annual crop income	Numeric (USD $hh^{-1}yr^{-1}$)
Total annual livestock income	Numeric (USD $hh^{-1}yr^{-1}$)
Total annual household income	Numeric (USD $hh^{-1}yr^{-1}$)
Total annual household margin	Numeric (USD $hh^{-1}yr^{-1}$)
Household vulnerability index variables	
Household head is disabled	Binary (1 = Yes)
Household possess a health insurance card	Binary (1 = No)
Household head has a regular source of income	Binary (1 = No)
Household head is elderly (over 70 years)	Binary (1 = Yes)
Household head has a chronic health condition	Binary (1 = Yes)
Household owns any land	Binary (1 = No)
Household land located in a politically volatile area	Binary (1 = Yes)
Vulnerability index	Numeric (Proportion of vulnerable outcomes expressed as a percentage of the sum of 7 variables)

2.8. Empirical framework for Covid-19 impact assessment

The study aimed to determine the causal effects of Covid-19 on farm outcome variables during the observational period (i.e., the average treatment effect on the treated, ATET). The treatment effect is defined as the difference between the mean outcomes for all farmers during the Covid-19 pandemic and the mean outcome of the same group of farmers before the Covid-19 pandemic. The outcome variables in the study included the total cropped farm area, fertilizer N use rate, the food consumption score, and the daily calorific intake for each household member. The farm socio-economic variables included gender, age of the household head, years of education of the household head, years of farming experience, farm tropical livestock units (TLU), household margins, use of hired labour, access to credit, access to agricultural information and membership in agricultural support groups.

Determining the effect of Covid-19 on-farm outcomes encounters the problem of sample selection bias resulting from observed and unobserved covariates. In typical cases, the effects of Covid-19 on household outcomes are influenced by the socio-economic characteristics of individual farm households. To better determine the Covid-19 impact, the treatment variable must be randomly assigned such that the impact of the covariate between the treated and the control groups are the same. Assuming that Y_{i1} is the farm outcome variable during Covid-19 and Y_{i0} is the outcome before the Covid-19 phase, according to Smith and Todd (2001), the Covid-19 impact on an outcome such as yield is derived follows.

$$\Delta Y = Y_{i1} - Y_{i0} \tag{1}$$

where ΔY denotes the Covid-19 impact on yield outcomes for a farm household. The mean difference is possible when individual farmers are concurrently evaluated during and after Covid-19. Since farms can be evaluated for Covid-19 impacts at a time, only one of the potential outcomes can be observed at a time, and simultaneous observation cannot be achieved. This presents the challenge of missing counterfactual data (Smith and Todd, 2005). The ATET, which focusses on the effect of Covid-19, has been used (Heckman et al., 1997). The ATET is the average difference in outcomes of farm households, with or without Covid-19 as expressed by Takahashi and Barrett (2013) as:

$$ATET \equiv E\{Y_{iA} - Y_{iN})|T_i = 1\}, \bullet = E(Y_{iA}|T_i = 1) - E(Y_{iN}|T_i = 1) \tag{2}$$

where *E{.}* was the expectation operator, Y_{iA} was the potential outcome during Covid-19 when the survey was undertaken (August 2021), while Y_{iN} was the potential farm outcome for the cropping season that preceded the Covid-19 pandemic in 2020. T_i was the treatment indicator 1 (referring to the Covid-19 period) and 0 (pre-Covid-19 phase). During Covid-19, it is not possible to observe farm outcomes under situations without Covid-19 ($E(Y_{iN}|T_i = 1)$). Yet, it is not plausible to replace these unobserved counterfactuals with pre-Covid-19 farm outcomes ($E(Y_{iN}|T_i = 1)$) as this is likely to result in biased ATET estimates (Takahashi and Barrett, 2013). This challenge can be addressed using the IPWRA estimation method proposed by Wooldridge (2010). The approach integrates regression adjustment (parametric or linear regression model) with propensity score weighting. The method is doubly robust because it only requires either the regression adjustment or propensity score model to be correctly specified.

Propensity score weighting methods have been proposed by Rosenbaum and Rubin (1983), where the propensity score or the probability of receiving treatment is expressed as:

$$p(X) = \Pr(T_i = |X) = F\{h(X)\} = E(T_i)|X) \tag{3}$$

where by X is a vector containing farm socio-economic characteristics, and $F\{.\}$ is a cumulative distribution function. Manda et al. (2018), used simple inverse weights equal to 1 for the treated and $\frac{\widehat{p}(X)}{1-\widehat{p}(X)}$ the non-treated, propensity weights can be defined as:

$$wi = T_i + (1 - T_i)\frac{\widehat{p}(X)}{1 - \widehat{p}(X)} \quad (4)$$

where $\widehat{p}$ are the estimated propensity scores. The ATET for the regression adjustment (RA) model can be specified as follows (Manda et al., 2018):

$$ATETRA = n_A^{-1}\sum\nolimits_{i=1}^{n} T_i[r_A(X,\delta_A) - r_N(X,\delta_N)] \quad (5)$$

where n_A was the number of farmers, $r_i(X)$ was the regression model during Covid-19 and Pre-Covid-19 *(N)* regressed on observed covariates X and parameters $\delta_i = (\propto_i, \beta_i)$. The estimator averages the predicted farm outcomes to estimate Covid-19 effects. The IPWRA estimator, an integration of Equations (3) and (4), are specified as follows:

$$ATETIPWRA = n_A^{-1}\sum\nolimits_{i=1}^{n} T_i\left[r_A^*(X,\propto_A^*) - r_N^*(X,\propto_N^*)\right] \quad (6)$$

2.9. Data analysis and presentation

The farm typology variables were summarized using means to describe cluster characteristics, and 1-way ANOVA was used to compare cluster characteristics. Regarding food security indicators (FCS and FIES), means were plotted (County × Covid-19 phase/ Typology × Covid-19 phase design). The FIES variables were graphically presented using a county*typology arrangement. Where appropriate, separation of means was implemented using the *agricolae* R package, first using the *aov* function (for ANOVA) followed by the *LSD.test* function (for mean separation). The IPRWA regression model was implemented using STATA version 15, to determine the impacts of Covid-19 on total cropped area, fertilizer N application rate, the food consumption score and daily calorific intake. The *teffects ipwra* regression STATA command was used, followed by *tebalance summarize* to check on covariate balance and *tebalance overid* for the overidentification test.

2.10. Ethical considerations

The survey followed ethical principles recommended by national and international best practice procedures. This included research ethical review process after which informed consent was obtained from interviewed farmers prior to the interviews. The survey respected the anonymity of participants and voluntary participation was maintained throughout the process. During the research, enumerators were trained on issues of professionalism, etiquette, respondent privacy, voluntary participation and disclosure, following standard research ethics principles (Oxfam International, 2018).

3. Results

3.1. Farm household characteristics and typology

Classification of farmers revealed three main clusters of farm households across the 5 Counties, including farm type 1 (36.7 %), farm type 2 (49.6 %), and farm type 3 (13.7 %) (Table 4). In all Counties, most of the farmers were in cluster 2 (42–56 %), followed by cluster 1 (30.8–40.3 %), while cluster 3 comprised the least proportion of farmers (9.7–21.0 %) (Table 4). The farm types defined the general wealth characteristics of farmers based on income structures and assets, including farm incomes, land and livestock ownership variables. Other variables included education qualifications, age and farming experience. The definitive income variable was household margins (FAO, 2018), signifying net annual household incomes. Type 1 described the poorest farmers, with a mean annual margin of US$ 1,772.4 in 2019, while type 2 farms represented medium wealth farms with a mean annual margin of US$ 2,048.1. Type 3 farms comprised the wealthiest farm households with an average annual household margin of US$ 7,782.9. Type 3 farms were also characterized by the highest educational attainments (12 years), TLU (4.7), total crop area (2.7 ha), annual crop income (US$ 867.9), livestock income (US$ 1,563.0), off-farm income (US$ 5,577.0), total household expenditures (US$ 3,827.3), and total annual income from all sources (USD 11,610.2). Type 1 farms recorded the lowest farming experience (7.1 years), TLU (1.1), annual livestock income (US$ 309.9), crop area (1.1 ha), crop income (US$ 146.3), off-farm income (US$ 1,316.3), low expenditure, and total annual household incomes (US$ 2,997.4). The household vulnerability index was lowest among farm type 3 (11.5 %) and twofold greater among the type 1 and type 2 farm households.

Table 4
Description of household typology and vulnerability characteristics across the 5 Counties.

Parameters	Farm cluster			Across farms	Sig
	1	2	3		
Number of households (%)	258 (36.7)	349 (49.6)	96 (13.7)	703 (100)	Na
Makueni County	53 (36.8)	71 (49.3)	20 (13.9)	144 (100)	Na
Nakuru County	44 (30.8)	81 (56.6)	18 (12.6)	143 (100)	Na
Kakamega County	52 (38.8)	69 (51.5)	13 (9.7)	134 (100)	Na
Siaya County	51 (37)	58 (42)	29 (21)	138 (100)	Na
Bungoma County	58 (40.3)	70 (48.6)	16 (11.1)	144 (100)	Na
Farmer wealth description					
TLU	1.1 ± 1.2	2.2 ± 1.9	4.7 ± 4.3	2.1 ± 2.5	0.000
Total crop area (ha)	1.1 ± 0.8	1.8 ± 1.9	2.7 ± 3.4	1.7 ± 2	0.000
Age of head	30 ± 8.5	52.7 ± 13.6	37.9 ± 15	42.4 ± 16.2	0.000
Years of education (yrs)	10.7 ± 2.5	7.7 ± 3.9	11.5 ± 3.5	9.3 ± 3.8	0.000
Years of farming experience (yrs)	7.1 ± 6.4	27.1 ± 14.3	13.2 ± 13.3	17.9 ± 15.1	0.000
Off-farm income (USD $hh^{-1}yr^{-1}$)	1,316.3 ± 1,269.0	1,214.0 ± 1,439.9	5,352.0 ± 4,610.1	1,816.6 ± 2,544.7	0.000
Livestock income (USD $hh^{-1}yr^{-1}$)	309.9 ± 349.4	602.1 ± 574.8	1,563.0 ± 1,362.4	626.1 ± 785.3	0.000
Crop income (USD $hh^{-1}yr^{-1}$)	146.3 ± 185.6	232.1 ± 382.8	867.9 ± 1,399.8	287.4 ± 636.7	0.000
Total annual income (USD $hh^{-1}yr^{-1}$)	2,997.4 ± 1,863.7	3,213.0 ± 2,394.4	11,610.2 ± 6,386.0	4,280.6 ± 4,260.4	0.000
Total annual expenditure (USD $hh^{-1}yr^{-1}$)	1,225.0 ± 887.7	1,164.9 ± 1,205.6	3,827.3 ± 2,975.6	1,550.5 ± 1,740.4	0.000
House-hold margin (USD $hh^{-1}yr^{-1}$)	1,772.4 ± 1,341.8	2,048.1 ± 1,597.7	7,782.9 ± 4089.3	2,730.1 ± 2,871.8	0.000
Vulnerability index (%)	20.7 ± 11.4	23.1 ± 11.5	11.5 ± 11.3	15.9 ± 11.3	0.000

1 US$ averaged Kshs 109.4 (CBK, 2021) during the survey period (August 2021), Na (not applicable); For farm typology distribution, values are frequencies and row percentages in parenthesis. Values are arranged as means ± standard deviations for wealth description variables.

3.2. Effects of Covid 19 on agricultural production and input use

Across all the farm clusters, 9–22 % of the farmers experienced Covid-19 challenges (Table 5). The proportion of farmers who experienced Covid-19 driven challenges was consistently higher in type 1 and 2 farms (29.3–57.9 %). The most important challenges faced by farmers included high input costs, poor access to fertilizers and pesticides, poor access to seeds, high labour costs and low farm output market prices. A higher proportion of type 1 and type 2 farmers experienced seed unavailability (43.2 %) compared to type 3 farmers (13.5 %) (Table 5). Further, the proportion of farmers who experienced fertilizer and pesticide unavailability due to Covid-19 was lowest in type 3, compared to type 1 and 2 farm households.

There was a significant linkage between improved seed use for different crops and Covid-19 phase. Farmers using improved seeds reduced from 76.5 to 65.7 % (cereals), 5.0–2.4 % (fruits), 14.9–7.0 % (legumes), 2.6–1.6 % (tubers) and 15.5–11.5 % (vegetables) (Figure 2a). The decline in use of improved seeds during the Covid-19 phase was evident across all the counties (Figure 2b) and farm types (Figure 2c). The greatest percentage declines in use of improved seeds were observed in type 1 and type 2 farms, while this was lowest in type 3 farms (Figure 2c). There was a significant change in the cropping areas between Covid-19 phases in Makueni, Kakamega, and Bungoma because their 95 % confidence intervals did not overlap (Figure 2e). The cropping areas were lower during Covid-19, relative to the pre-Covid-19 phase (Figure 2f) across all farm types.

Fertilizer N rates decreased by 6 % across Counties, while the average expenditure on fertilizers decreased by 15 %. Contrariwise, farmers increased their manure application rates by 33 % and related expenditure by 129 % across the sites (Table 6). Regarding fertilizer use rates, all counties recorded a decline except Makueni County, which recorded a 51 % increase in fertilizer use rates. The farm expenditure on fertilizers recorded a significant difference by Covid-19 phase and county. Highest per unit area fertilizer expenditures were observed in Bungoma (127.5 USD ha^{-1}). Across the 5 counties, cumulative manure use during the Covid-19 period increased by 33 %, with application on fewer fields (<80 %) at higher rates (data not shown). Such higher manure application rates were more common (50–70 %) in fields closer to homesteads than those further away. The higher manure application rates were partly an adaptation to offset the reductions in fertilizer availability and accessibility (Table 6). Over 70 % of surveyed farmers attributed higher manure application rates to fields closer to homesteads relative to further away fields, to the bulk nature of manure and implications for transportation cost coupled with easier access to food grown in closer fields for household consumption during the period of restricted movement.

The crops for which manure and fertilizers were applied differed with counties. In Siaya, Kakamega and Bungoma counties between 75 and 80 % of all manure and fertilizers were targeted to the maize crop, while the rest was targeted to vegetables and fruit trees. In Nakuru county, 60 % of all applied manure and fertilizers were on potato fields, 35 % on maize fields and the remaining 5 % on vegetables and fruit trees. In Makueni, about 70 % of manure and fertilizer was applied on mangoes and citrus fruit trees, 20 % on vegetables and 10 % on maize plots. Although a range of root crops were common in all the 5 counties, other than potato in Nakuru, manure and fertilizer application to support other common root crops like cassava, arrow roots, and yams was negligible. Similarly, the application of manure and fertilizers on plots grown with legumes was negligible. These differences in allocation of manure and fertilizers are indicative of purpose for crop cultivation and climate. In the western Kenya counties (Siaya, Kakamega and Bungoma), the production is largely subsistence and maize meal “Ugali” is the staple food (Mulwa et al., 2009). In Nakuru, maize is an important staple crop but, Nakuru is also one of the largest potato producing counties in Kenya. The higher productivity, market value, and higher nutrient demands for optimal production of potatoes drove farmers to allocate more fertilizers and manure to potato production. The highest manure and fertilizer allocation to mangoes and citrus fruits in Makueni is driven by good performance of fruit trees coupled with higher commercial value (Maundu, 2020). Makueni, is a semi-arid county characterized by low performance of cereals but excellent performance of deeper rooting fruit trees which are more resilient to moisture stress.

Table 5
Impact of Covid-19 on agricultural productivity during the Covid phase.

Covid-19 effects	Farm type			Response n
	1	2	3	
Higher cost of inputs	175 (35.9)	249 (51.1)	63 (12.9)	487
Fertilizer and pesticide unavailability	58(36.5)	81(50.9)	20 (12.6)	159
Seed unavailability	64(43.2)	64(43.2)	20 (13.5)	148
Higher cost of labour	49(35.0)	70(50.0)	21 (15.0)	140
Low farm output prices in the market	41(29.3)	67(47.9)	32 (22.9)	140
Delays in planting	39(34.8)	57(50.9)	16 (14.3)	112
Low demand in the market	30(30.0)	51(51.0)	19 (19.0)	100
Delays in harvesting	23(35.4)	34(52.3)	8(12.3)	65
Difficulties in accessing credit facilities	23(40.4)	29(50.9)	5(8.8)	57
Reduced incomes (farm + off-farm)	12 (40)	14(47)	4(13.3)	30
Reduced access to extension services	10(38.5)	13(50.0)	3(11.5)	26
Inadequate labour	6(31.6)	11(57.9)	2(10.5)	19

Values are row frequencies and percentages (in parenthesis) calculated based on response n.

3.3. Access to agricultural extension services

During the pre-Covid phase, 72 % of the farmers received information from multiple sources (Table 7). The prevalence of access to information from these sources declined by 51.4 % during the Covid-19 phase (Table 7). All the farm types observed a significant information decline (Data not shown). The three farm types used similar information sources with extension, NGOs and farmer-to-farmer as the key information sources for over 60 % of the farmers across the 3 farm categories. The largest declines in information sources during Covid-19 included faith based organizations- FBOs (−100 %), research organizations (−87.5 %), agro-companies (−80.9 %), community based organizations-CBOs (−67.7 %), extension (−65.3 %), NGOs (−51.2 %), farmers (−36 %), agro-dealers (−34.2 %), media (−28.5 %), farmer field schools (−20 %), while there was an increase in family/ friends inter-personal sources (+28.5 %) across the Counties.

There were differences in information access by farmers in the different Counties. Farmers in Bungoma and Makueni received information from 10 different sources, including NGOs, farmers, and extension services. Nakuru County received agricultural information from 9 different sources, which mostly included extension services, while Kakamega and Siaya received information from the least diverse sources. In Kakamega County, farmers mostly received information from NGOs and fellow farmers, while in Siaya County, the predominant sources included NGOs and Agrodealers. The study revealed significant Chi-square associations between Covid-19 phases and changes in information access in Makueni and Nakuru County. Except for Bungoma, where the decline in information access from public extension workers was considered low at 38 %, the decline in information access from public extension ranged between 66 % and 83 % in the other 4 Counties (Table 7). Counties with higher declines in extension activity during the Covid-19 phase tended to record higher Covid-19 prevalence, including

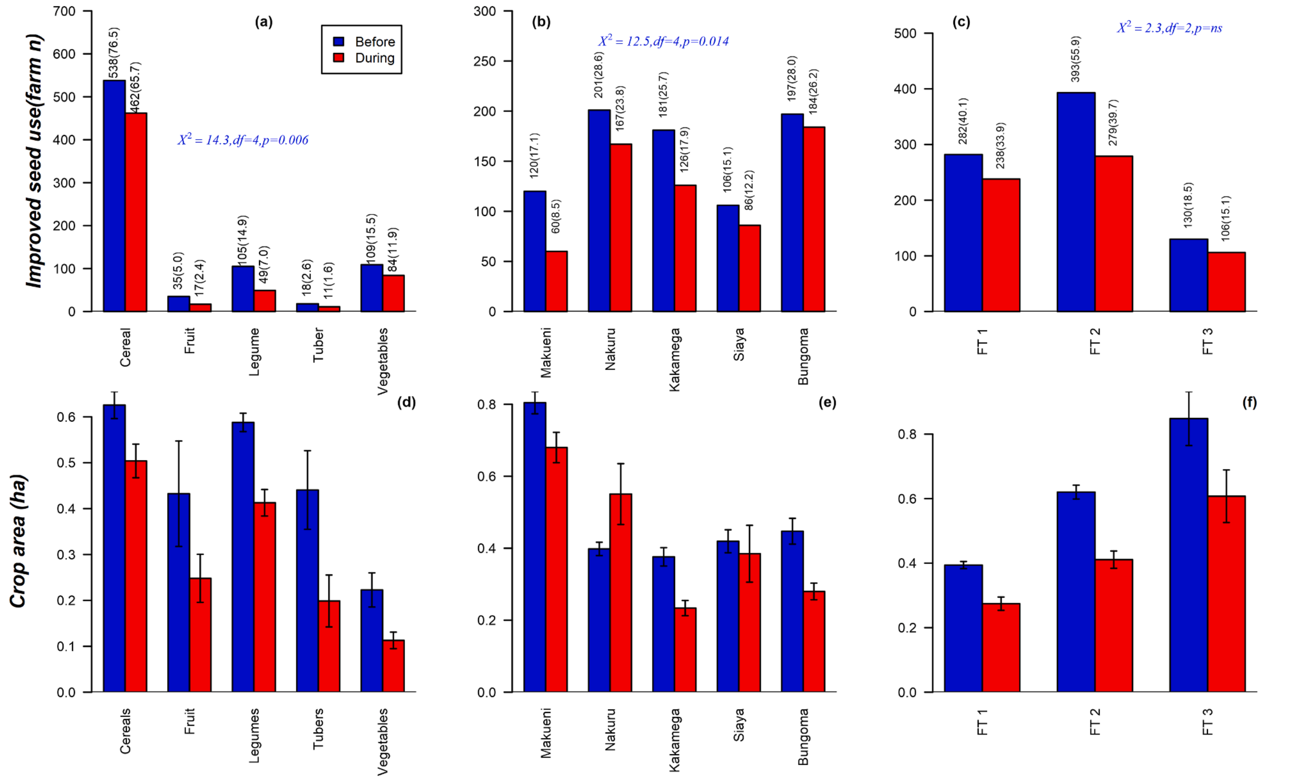

Fig. 2. Number of farms using improved seeds by crop category and Covid-19 phase (a), County and Covid-19 phase (b) and by farm type and Covid-19 phase (c); values are number of farms and percentages (parenthesis). Mean crop area by crop category and Covid-19 phase (d), County and Covid-19 phase (e), and by farm type and Covid-19 phase (f). Error bars are 95% confidence intervals. Pairwise error bars that are not crossing are significantly different.

Table 6
Fertilizer and manure use during the Pre-Covid-19 and Covid-19 phase by Counties and farm type.

County, Typology, Covid-19 phase		Inorganic nitrogen applied (kgN/ha)	Expenditure on fertilizer (USD ha^{-1})	Animal manure applied (t/ha)	Expenditure on manure USD ha^{-1})
All farms	Pre-Covid	40	102.3	2.4	1.4
	During	37.6	86.8	3.2	3.2
	Percent change	−6.10 %	−15.10 %	33.30 %	128.60 %
County*Period					
Makueni	Pre-Covid	23.2 e	74.9c	2.1b	1.9 cd
	During	35.1 cde (51.3 %)	47.6 ab(−36.4 %)	3.1 ab (47.6 %)	2.3 cd(21.1 %)
Nakuru	Pre-Covid	33.9 cde	89.8 bc	2.02b	–
	During	30.7 de (−9.4 %)	88.9 bc (−1.0 %)	1.96b (−3.0)	0.8 a
Kakamega	Pre-Covid	45.3 ab	109.6b	2.7b	0.1 d
	During	40.6 bc (−10.4)	74.6b (−31.9)	4.1 a (51.9 %)	0.5 d (400 %)
Siaya	Pre-Covid	36.6 cd	93.3 bc	3.0 ab	5.3 bc
	During	31.2 de(−14.8 %)	80.1 bc (−14.1 %)	2. 5b(−16.7)	8.9 ab (67.9 %)
Bungoma	Pre-Covid	52.6 a	127.5 a	2.4b	0.4 d
	During	50.3 a (−4.4 %)	117.8 a (−7.6 %)	2.7b (12.5 %)	0.6 d (50.0 %)
Farm type* Period					
Farm type 1	Pre-Covid	42.2 a	105 a	2.6ab	2.2b
	During	39.8 a (−5.7)	92.2 a (−12.2)	3.3a	5.3 a
Farm type 2	Pre-Covid	38.3 a	100.6	2.4ab	0.9b
	During	35.8 a (−6.5)	84.1 a (−16.4)	3.2 a(33,)	1.7b (88.9)
Farm type3	Pre-Covid	40.5a	101.4a	2.2ab	1.2b
	During	37.9 a (−6.4)	82 a (−19.1)	2.7ab(22.7)	2.7 ab (125.0)

A negative % value indicates a proportionate decline, while positive % values indicate a proportionate increase. Column means followed by the same letter are not significantly different.

Siaya (83 % decline) and Makueni (79 %).

3.4. Food security, dietary diversity and coping strategies

3.4.1. Impact of Covid-19 on food security

Across all the farm types, a substantial number of farmers were worried about not having enough food (Figure 3). In all assessments of household food sufficiency and resources to acquire food, there was a lower proportion of type 3 farmers who were worried about not having enough food (43 % of farmers) compared to type 1 (70 %) and type 2 farmers (71 %) across Counties (data not shown). Farm type 3 households also recorded the lowest proportion of farmers who either consumed non-preferred foods, slept hungry or went a whole day without food relative to type 1 and 2 farmers.

Table 7
Sources of agricultural information before and during Covid-19 by County.

Source	Makueni		% change	Nakuru		% change
	Pre-Covid-19	During Covid-19		Pre-Covid-19	During Covid-19	
Agro-companies	5(4.1)	6(13.3)	20.0	4(2.8)	1(1.6)	−75.0
Agro-dealer	10(8.1)	4(8.9)	−60.0	5(3.5)	5(7.8)	0.0
CBOs	8(6.5)	1(2.2)	−87.5	2(1.4)	1(1.6)	−50.0
Extension	38(30.9)	8(17.8)	−78.9	91(64.1)	31(48.4)	−65.9
Family/friends	7(5.7)	4(8.9)	−42.9	11(7.7)	2(3.1)	−81.8
Farmers	30(24.4)	10(22.2)	−66.7	9(6.3)	12(18.8)	33.3
FBOs	–	–		1(0.7)	(0.0)	−100.0
FFS	4(3.3)	0	−100.0	–	–	–
Media	–	2(4.4)		5(3.5)	5(7.8)	0.0
NGOs	10(8.1)	5(11.1)	−50.0	14(9.9)	7(10.9)	−50.0
University/research	11(8.9)	5(11.1)	−54.5	–	–	–
Total N	123	45	–	142	64	–
	Kakamega			**Siaya**		
Agro-companies	1(1.6)	0(0.0)	−100.0	14(22.6)	13(44.8)	−7.1
Agro-dealer	1(1.6)	0(0.0)	−100.0	–	–	–
CBOs	4(6.3)	2(10.5)	−50.0	2(3.2)	1(3.4)	−50.0
Extension	4(6.3)	1(5.3)	−75.0	18(29.0)	3(10.3)	−83.3
Farmers	8(12.5)	2(10.5)	−75.0	5(8.1)	3(10.3)	−40.0
FBOs	–	–		1(1.6)	(0.0)	−100.0
FFS	3(4.7)	0(0.0)	−100.0	–	–	–
NGOs	43(67.2)	14(73.7)	−67.4	22(35.5)	9(31.0)	−59.1
Total N	64	19	–	62	29	–
	Bungoma				**Across Counties**	
Agro-companies	3(2.6)	5(6.3)	66.7	21(4.1)	4(1.7)	−81.0
Agro-dealer	6(5.1)	5(6.3)	−16.7	38(7.5)	25(10.5)	−34.2
CBOs	11(9.4)	9(11.3)	−18.2	31(6.1)	10(4.2)	−67.7
Extension	24(20.5)	15(18.8)	−37.5	173(34.1)	60(25.3)	−65.3
Family/friends	6(5.1)	2(2.5)	−66.7	14(2.8)	18(7.6)	28.6
Farmers	24(20.5)	20(25.0)	−16.7	75(14.8)	48(20.3)	−36.0
FBOs	1(0.9)	(0.0)	−100.0	3(0.6)	0 (0)	−100
FFS	1(0.9)	1(1.3)	0.0	5(1.0)	4(1.7)	−20.0
Media	–	–	–	7(1.4)	5(2.1)	−28.6
NGOs	40(34.2)	22(27.5)	−45.0	125(24.6)	61(25.7)	−51.2
University/research	1(0.9)	1(1.3)	0.0	16(3.1)	2(0.8)	−87.5
Total N	117	80	–	508	237	–

Notes. CBOs (Community Based Organizations), FBOs (Faith Based Organizations), FFS (Farmer Field Schools), and NGOs (Non-Governmental Organizations). Values are frequencies and column percentages (in parenthesis).

The relationship between perception of food security and resource endowment was not linear as type 2 farms recorded either higher or similar proportion of households worried about insufficient food relative to type 1 farms (Figure 3a). The type 2 farms also recorded the highest proportions of households (48.4–61.4 %) which did not consume preferred foods or consumed limited food due to lack of resources (Figures 3b, 3c) in 4 of the 5 Counties. Except for a few cases (2 farmers or < 1 %) in Kakamega County, there were no type 3 farmers who went without food for a whole day due to lack of food (Figure 3i). In all FIES assessments (Figure 3a-3i), type 3 farmers recorded the lowest proportions of farmers (0 %-19.4 %), who experienced food insecurity due to lack of food or resources to acquire food.

3.4.2. Food consumption score (FCS) and daily calorific food intake

The Food Consumption Score (FCS) was calculated using the frequency of consumption of different food groups by a household seven days prior to the survey. The FCS is a proxy indicator of household caloric availability (Weismann et al., 2009). Mean observations for all the FCS ranged between 69 and 110, and on average, the reviewed farm categories and Counties were within the threshold of acceptable consumption before and during the Covid-19 period. However, there was a decline in the FCS during the Covid-19 phase compared with the pre-Covid-19 period (Figure 4a and 4b) for all Counties and farm types.

In all the Counties, farm type 3 holdings, consistently recorded higher food consumption scores, compared to farm type 1 and type 2 farm households. In aggregate, the FCS declined from 83.1 to 77.7 on all farms. The FCS declined by 14.9 % in Kakamega, 9.1 % in Makueni, 3.8 % in Bungoma, 1.8 % in Siaya, and 1.2 % in Nakuru (Figure 4a). Within farm types, percentage declines were 7.2 % (type 3), followed by 7.0 % (type 2) and 6.9 % (type 1). Significant decline in FCS during the Covid-19 phase was observed in Kakamega County. For other counties, the differences in FCS before and during Covid-19 were not significant. There was a positive relationship between the FCS and household margins, in both Pre-Covid (Figure 4c) and during the Covid-19 phase (Figure 4d).

The calorific values met the recommended daily calorie requirements of between 2,000 and 2,500 for both pre and during covid in the counties of Siaya, Kakamega and Bungoma (Fig 5a). Based on recommended daily calorific intake, the intakes were lower than the recommended level in Makueni and Nakuru pre and during Covid-19. The average calorie consumption by farm households was highest in farm type 3 holdings (averaging 2,063 calories per person^{-1} day^{-1}), followed by farm type 2 (1,823) and type 1 farm (1,717) across farms in all Counties (Fig 5b).

Across the counties, the highest and significant ($p < 0.05$) reduction in food calories consumed per day by farmers during the Covid-19 period included fish (−12.3 %), meat (−10.6 %), sugar (−9.5 %), oil (−8.4 %), and cereals (−5.8 %) (Table 8). Reductions in consumption of eggs (−3.3 %), legumes (−2.0), and fruits (−0.8) food calories were also observed. The vegetable and root/ tuber calorific intake values increased.

The daily calorific intake values recorded significant reductions after Covid-19, mostly among type 1 and 2 farmers (see *Supplementary Materials 1*). Type 1 farmers recorded a significant decline (8.5 %) in daily meat calorie intake. For sugar and oil daily calorific intake, type 1 and type 2 farms recorded significant declines of 10 % and 8.4 %,

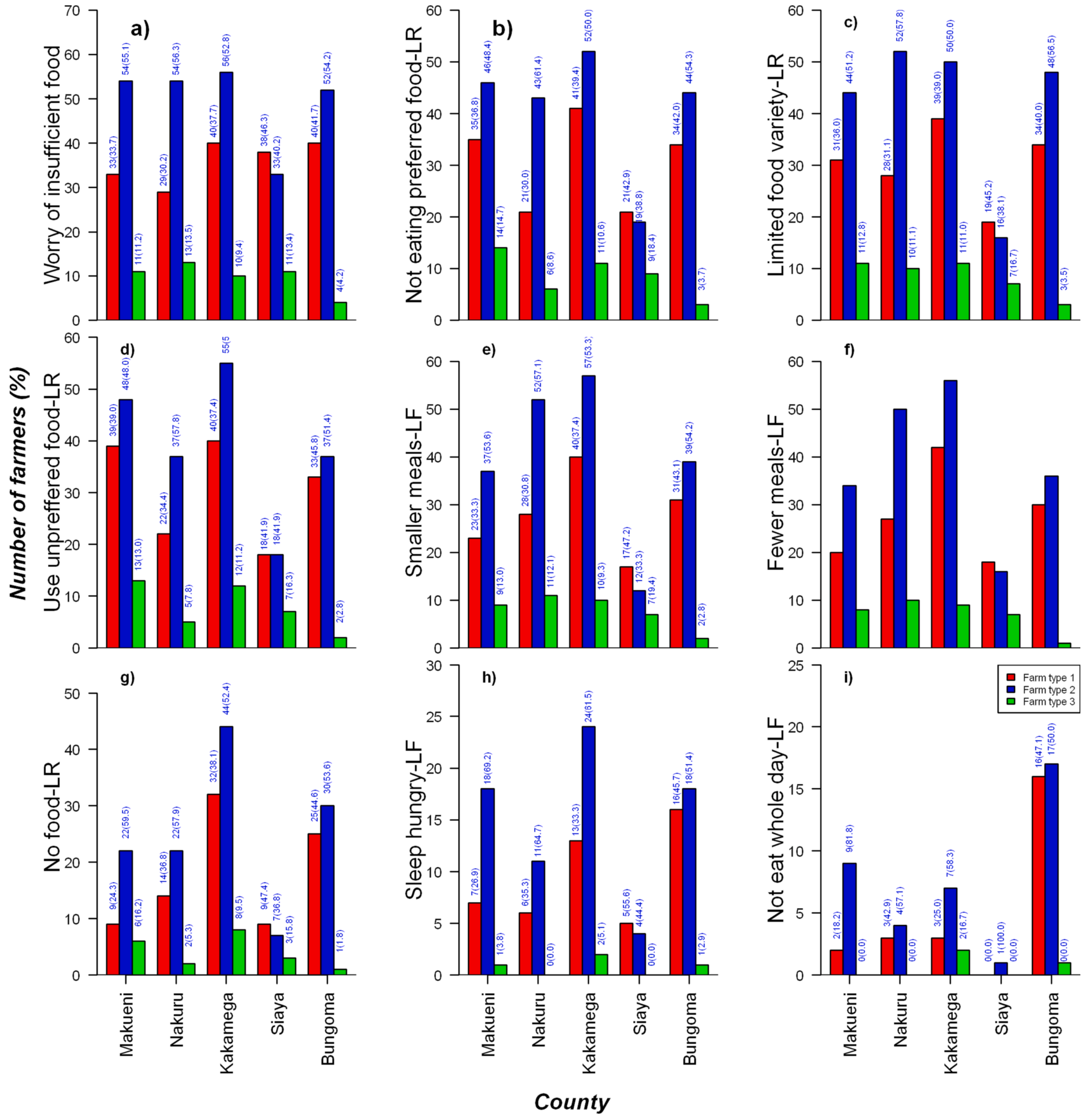

Fig. 3. Household food sufficiency during Covid-19, faceted by farm clusters and county for different FIES parameters (3a to 3i). Values are presented as frequencies followed by percentages (in parenthesis) calculated for farm types based on County effective responses. Variable descriptions have been abridged due to space considerations, and main clauses have been completed by subsidiary clauses as follows: - LR (due to lack of resources), and -LF (due to lack of food).

respectively, during Covid-19. The cereal calorific intake values declined significantly by 6.5 % among type 1 farms. In contrast, there was no significant change in calorific intakes of fish, meat, sugar, oil, and cereals during Covid-19 among the type 3 farm households. The type 3 farms recorded highest daily caloric intake values pre-Covid in all food classes and used the highest calories in all food categories, except cereals during the Covid-19 (*Supplementary Materials 1*).

3.4.3. Coping strategies for the impact of Covid-19 on food security

The thirteen coping strategies identified by farmers have been ranked based on the magnitude of their frequencies (Table 9). Based on frequencies, the importance of different strategies varied from 0.4 to 51 % (Table 9). For all the Counties, the sale of livestock/poultry was farmers' most important (widely used) Covid-19 coping strategy (51.4 %). This was followed by borrowing from family/friends (27.6 %), borrowing from mobile phone service providers and financial institutions (banks and SACCOs) (25.2 %), remittances (17.6 %), crop diversification (15.9 %), selling labour (51.2 %), and selling assets (7.4 %). A lower proportion of type 3 farms relied on more drastic coping strategies during Covid-19 compared to type 1 and 2 farms. For example,

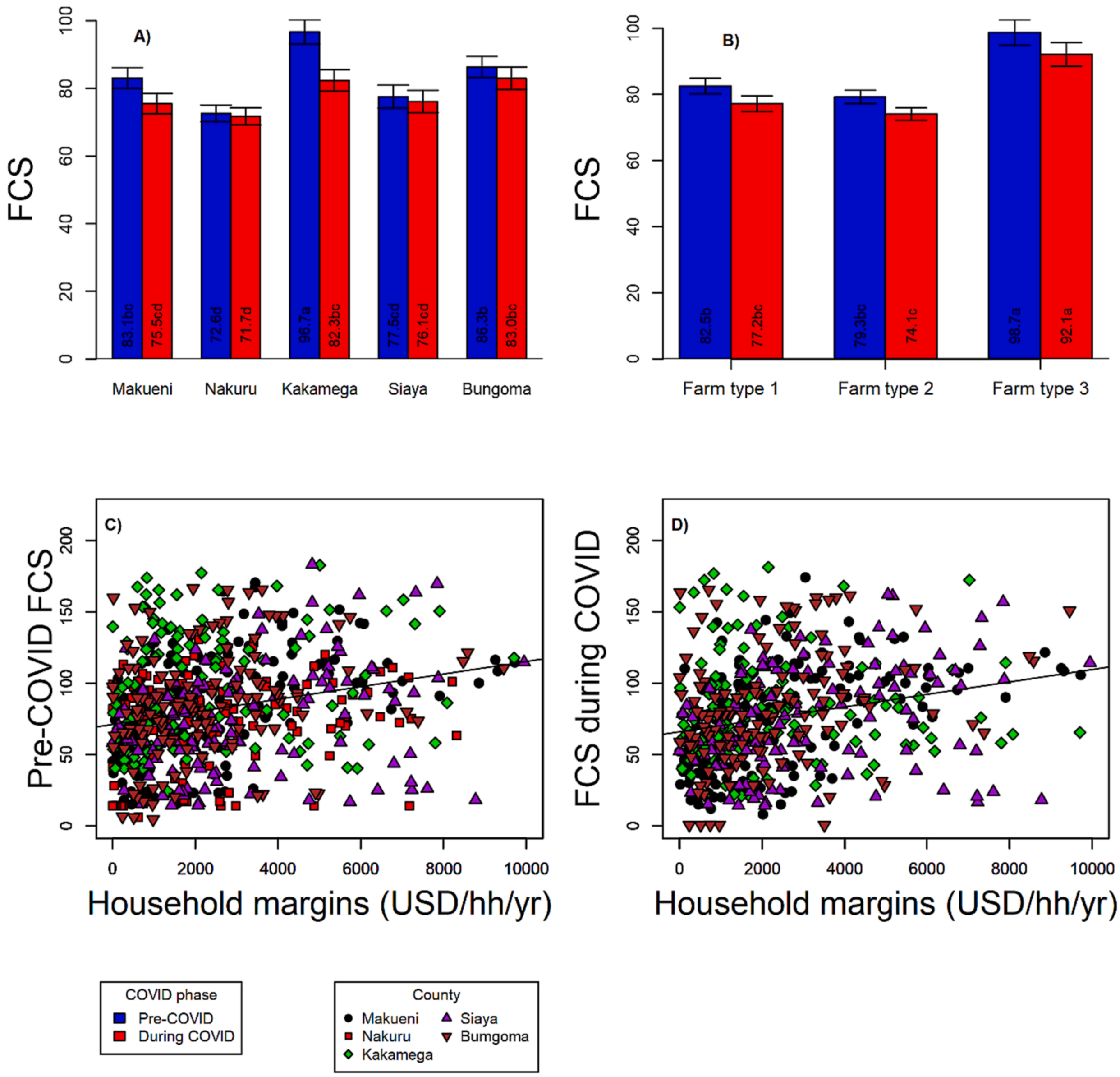

Fig. 4. Mean food consumption score values (FCS) by county (4a) and farm types (4b) and regression between household margins and the FCS Pre-Covid-19 (4c) and during Covid-19 (4d). Means with similar letters (4a and 4b) are not significantly different based on interaction LSD post hoc tests.

proportionally lower type 3 farmers sold household assets, offered labour, or borrowed from friends or mobile phone credit providers. The findings further show that type 3 farmers recorded the lowest proportion of farmers who relied on remittances, remained hungry or made use of food aid (Table 9).

3.5. Covid-19 impacts on farm outcomes

This section reports the potential outcome means and the ATET (average treatment effects on the treated) results for Covid-19 effects on the total cropped area, fertilizer application rates, the food consumption score (FCS) and the daily calorific intake per household member (Table 10).

Equations (1) to (6) (section 2.8) show how the parameters were modelled to generate the potential outcome means and the ATET. For all parameters, the covariates were balanced, and the overidentification tests were adequate in the model (Chi-square = 3.117, p = 0.960). The results indicated that there was a decline in all farm outcome parameters. The mean crop area indicated that the Covid-19 onset negatively affected agricultural activity and decisions with a significant reduction in nitrogen fertilizer application rates, which on average reduced from 30.1 kgN/ha to 25.8 kgN/ha. There was however no significant changes in cropped areas. Similarly, there was a significant reduction in the average food consumption score from 58.0 to 24.3, while the calorific intake values declined significantly too.

4. Discussions

4.1. Covid-19 impacts on farm types

Farm typology classification in this study generated three distinct farm types that defined the general wealth characteristic of farmers in the study areas. The three farm types significantly differed in key variables for farm typology construction (FAO, 2018), including household income structure, land size holdings, educational attainments, and livestock ownership. Middle-income farms (farm type 2) accounted for the largest proportion (50 %) of surveyed households, followed by low-income farms (farm type 1) at 37 % of households, and wealthy farm

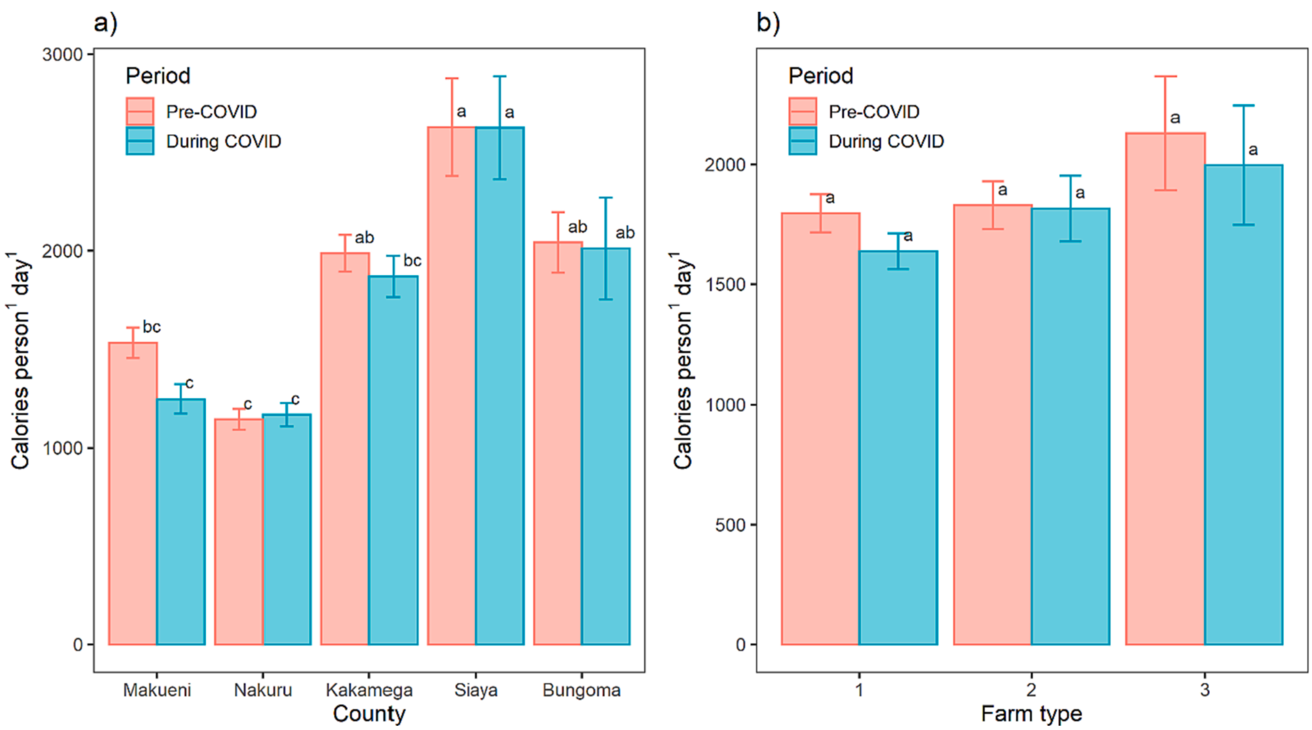

Fig. 5. Food calorific intake (all foods) before and during Covid-19 by County (a) and farm type (b). The error bars are standard deviations, while pairwise means followed by the same letter are not significantly different.

Table 8
Change in food calories consumed by different food classes (Calories person^{-1} day^{-1}) across farms.

Food class	Pre-Covid-19	During Covid-19	% Change	Sig
Fish	44.7	39.2	−12.3	0.030
Meat	42.5	38	−10.6	0.017
Sugar	141.4	127.9	−9.5	0.000
Oil	192.1	175.9	−8.4	0.001
Cereals	111.3	104.9	−5.8	0.017
Eggs	12.1	11.7	−3.3	ns
Legumes, nuts and seeds	78.4	76.8	−2.0	ns
Fruits	72.2	71.6	−0.8	ns
Milk and milk products	94. 0	94.0	0.0	ns
Vegetables	93.7	95.2	1.6	ns
Roots and tubers	77.9	83.2	6.8	ns

Table 9
Farmer strategies for coping with Covid-19 driven hunger, faceted by farm clusters.

Coping mechanisms	Farm type†			Total*
	1	2	3	
Sell livestock/poultry	123 (34.1)	186 (51.5)	52 (14.4)	361 (51.4)
Borrow (friends, relatives)	73 (37.6)	105 (54.1)	16(8.2)	194 (27.6)
Borrow (financial institutions, mobile phones)	71 (45.8)	85 (54.8)	21 (13.5)	177 (25.2)
Remittances from relatives	43 (34.7)	72 (58.1)	9(7.3)	124 (17.6)
Crop diversification	36 (32.1)	60 (53.6)	16 (14.3)	112 (15.9)
Sell farm labour	42 (39.3)	57 (53.3)	8(7.5)	107 (15.2)
Sell household assets	17 (32.7)	31 (59.6)	4(7.7)	52(7.4)
Missed some meals	20 (42.6)	17 (36.2)	10 (21.3)	47(6.7)
Harvest wild fruits	9(20.5)	28 (63.6)	7(15.9)	44(6.3)
Remain hungry most of the time	14 (48.3)	13 (44.8)	2(6.9)	29(4.1)
Relied on savings	1(12.5)	3(37.5)	4(50.0)	8(1.1)
Relied on relief food/donations	2(40.0)	3(60.0)	0(0.0)	5(0.7)
Income diversification	1(33.3)	2(66.7)	0 (0.0)	3(0.4)

† The values for farm type are arranged as frequencies and row percentages (in brackets) calculated based on effective responses. * The values are effective response n followed by column percentages (in brackets) based on the sample size (703).

households (farm type 3) at 14 % of households surveyed. Covid-19 affected farm types 1 and 2 more negatively than farm type 3. The results herein attribute this to better resilience, especially related to higher incomes enabling farm type 3 to access agricultural inputs and services even during Covid-19 than farm types 1 and 2.

The structural variables were different between farm types. The type 3 farms recorded 339 % and 280 % higher margins relative to type 1 and type 2 households respectively. Type 3 farms also recorded highest TLU (327 % and 114 %), crop area (145 % and 50 %), education years (7.5 % and 49.3 %), and total household incomes (287 % and 261 %) relative to type 1 and type 2 households respectively. There was also a large difference in livestock incomes (404 % and 160 %) among type 3 farms, relative to type 1 and type 2 farms respectively. In addition, the vulnerability index was lowest in type 3 farms, relative to type 1 and 2 farm households. The Covid-19 disruption is likely to impact different farm types differently. Swinnen (2020) pointed out that Covid-19 is likely to manifest disproportionate impacts on poor households' income, food and nutrition security. The wealth status indicators and educational levels are critical drivers for household resilience in developing countries. Wealthier families are likely to access commodities from the market by using financial resources or in exchange with other farm commodities. Furthermore, higher education provides farmers with better chances to participate in off-farm activities like off farm employment. This significantly increases the resilience capacity of

Table 10
Causal effects of Covid-19 on farm outcome variables.

Outcome variables	Covid phase	PO means	Robust std error (sig)	ATET (1 vs 0)	Robust std error (sig)
Cropped area (ha)	Pre-Covid-19	1.37	0.052***	−0.083	0.071 ns
	During Covid-19	1.28	0.049***		
Fertilizer N application rate (kg N/ha)	Pre-Covid-19	30.1	1.5***	−4.791	2.059*
	During Covid-19	25.8	1.2***		
FCS	Pre-Covid-19	58	1.8***	−36.658	2.522***
	During Covid-19	24.3	1.6***		
Calories day^{-1} person^{-1}	Pre-Covid-19	1475.9	27.7***	−146.01	40.14***
	During Covid-19	1330.1	27.3***		

Significant at 0.001 (***), 0.05 (*), PO is potential outcome means.

wealthy farm households compared to less wealthy farmers.

4.2. Covid-19 impacts on access and use of agricultural input and extension services

Type 3 households were less adversely affected by Covid-19 in terms of agricultural input use as they were characterized by higher levels of resource endowment. Type 3 farms were also less likely to experience delays in harvesting and planting because the group was not resource constrained to acquire planting inputs and farm labour. This farm type also experienced less challenges to access credit, due to ownership of larger tracts of land, livestock ownership, and ownership of higher value capital equipment, which provide better security and collateral necessary to acquire diverse loan products from financial institutions. Additionally, farm type 3 households recorded a lower decline in planted crop areas compared to type 1 and 2 households, partly because they had better access to agricultural inputs, financial resources, and labour at the beginning of the planting season compared to type 1 and 2 farms.

Crop production is a lengthy process that includes planting, weeding, pesticide applications, harvesting and transporting farm inputs and outputs, involving labour and investments at various stages (Workie et al., 2020). The dependence on each production factor can differ significantly in different farm systems and farm types. Nchanji et al (2021) found that Covid-19 restrictions negatively impacted on the availability and cost of farm inputs and labour for bean production in Eastern and Southern Africa.

The increment in manure use rates during the Covid-19 phase was an adaptation by farmers to mitigate the costs of fertilizers, and the poor access to fertilizers during Covid-19. The likely source of manure was accumulation (in cattle sheds/ kraals) from previous months/seasons preceding the Covid-19 phase. There was evidence that increased manure application rates coincided with reduced field sizeswhere farmers applied it and most of such inputs were applied to the fields closer to homesteads as opposed to fields that were further away. Over 95 % of farmers surveyed for this study practice either semi-intensive or intensive livestock production systems, implying that manure is generated close to the homesteads. The higher rates of manure application in smaller fields closer to homesteads, points to deliberate manure intensification within selected farm niches to increase productivity and reduce costs (Rotich, 2022). The manure and other organic resources were often more available and affordable plant nutrition sources for most of the smallholder farmers during the Covid-19 lockdown. A global analysis of fertilizer trade networks showed that organic fertilizers were in higher demand during Covid-19 because they provided an option to address the challenge of rising fertilizer costs (Gutiérrez-Moya et al., 2023). Similarly, in Sri-Lanka, farmers increased use of organic manure, due to challenges of accessibility of inorganic fertilizer (Peace Winds America, 2020; Rathnayake et al., 2022).

There was a decline in improved seed use across different crops and farms. For cereals especially maize, the reduction was marginal compared to that observed for legumes. The lower reduction in the use of improved seeds observed for cereals is partly related to cereals' role as a key food security crop in Kenya. Consequently, the production and distribution of cereal seed coupled with advisory for cereal crop production receives most support from the government and other stakeholders. A regional assessment of Covid-19 impacts on bean production showed that owing to government Covid-19 control restrictions, the resultant decline in access to farm labour, agricultural finance, agricultural inputs and output markets had a major effect on bean production in Southern Africa. This agrees with our study, showing that high input costs, farm input unavailability (fertilizers, seeds, pesticides), labour costs, and low market prices were the main production challenges faced by farmers during the Covid-19 period. Our study findings are congruent with results generated from other regions. For example, Iese et al. (2021) reported a limited supply of planting materials for vegetables, non-seed crops and fruit trees in the Fiji Islands. The widespread similarity in these results, especially within the developing economies, relates to lack of adequate policy frameworks and poor seed support systems for disruptions such as Covid-19.

The Covid-19 pandemic reduced access to agricultural information by farmers. This was higher for external and communal information sources, including faith-based organizations (FBO), farmer field schools (FFS), and government extension services. Meanwhile, local-interpersonal sources of information recorded lower decline in use as information sources during the Covid-19 pandemic. The higher reductions in FBO and FFS sources were likely because the Covid-19 regulations in Kenya restricted large gatherings like farmer's field days and other important social events such as burials and religious gatherings. Subsequently, farmers relied more on local-interpersonal sources of information, including other farmers and family members, to fill the information gap. Meanwhile, the media increased its responsibility to deliver agricultural information to reduce the local Covid-19 transmission risk especially in Nakuru County which recorded a proportionate increase in media use among farmers. This was consistent with the high Covid-19 levels in Nakuru County which was included in a partial government lockdown of five Covid-19 Hotspot Counties in Kenya (Kiambu, Nairobi, Nakuru, Machakos and Kajiado) in March 2021. Our findings align with an earlier study in India, where 27 % of women indicated that their regular sources of information were unavailable or inaccessible due to Covid-19 lockdowns (Alvi et al., 2021). Similar to the situation in Kenya, Covid-19 related lockdowns in India led to reduced dependence on community-based types of information sources such as group meetings and field days, with a greater reliance on local-interpersonal sources of information, including farmer networks consisting of family and friends (Alvi et al., 2021).

Besides lockdown restrictions, agricultural extension officers faced additional challenges during the Covid-19 pandemic, such as lack of sufficient Covid PPE (Personal Protective Equipment), movement challenges, and restriction of gatherings. Furthermore, with 50 years as the average age of Kenya extension workers (MOALFC, 2022), many extension workers were indirectly blocked from service delivery interactions due to age-related complications, which would predispose such workers to profound Covid-19 health effects. These factors presumably explain the higher decline in extension dissemination that was observed in higher-Covid-19 prevalence Counties, including Nakuru, Makueni and Siaya Counties.

4.3. Impacts of Covid 19 on food security

The survey findings suggest that the Covid-19 effects among small-scale farmers in Kenya were asymmetric, with wealthier farm households coping better with the Covid-19 pandemic than poor farm households. In relation to coping with hunger, the study recorded a lower proportion of farmers in type 3 who employed more drastic coping measures, including selling assets, exchanging labour, or borrowing from various sources to cope with food shortages. The study also found a lower proportion of type 3 farms that relied on remittances compared to other farm types, while none of the type 3 farmers used food relief or donations to cope with Covid-19 impacts. Ashford et al. (2020) observed that the economic slowdown resulting from Covid-19 has reinforced existing societal inequities in many countries, thus affecting access to basic needs, including food, water and health services. The pandemic also negatively impacted access to jobs and livelihoods for several farming and non-farming households, influencing food security and nutrition (HLPE, 2020).

The lower decline in calorific intake for type 3 compared to type 1 farms can be explained by the fact that the more resource-endowed farm types were in a better position to acquire food products and were thus more resilient to the effects of the Covid-19 pandemic. The survey's findings are supported by Swinnen (2020), who observed that vulnerable households were likely to experience higher risks of food crisis, compared to wealthier regions and households. The less wealthy farm households depend highly on selling physical labour in various types of casual employment, which was affected by the pandemic due to the curfews and lockdown restrictions. In Bangladesh, Mandal et al. (2021) found that low-income households tended to lose a higher proportion of income during the first 100 days of Covid-19 restrictions, while incomes of wealthier segments were less affected. The same was corroborated by Amare et al. (2021) in Nigeria.

The reduction in consumption of nutritionally dense foods such as fish, meat, sugar, and oil during Covid-19 was expected, as corroborated in previous studies (e.g., Kansiime et al., 2021). As with other vulnerabilities, these reductions were more prevalent in farm types 1 and 2 than in farm type 3. This happened against the contrasting need for such foods to support the development of more effective immune systems against Covid-19 infections. The observed increase and stability in legume and milk consumption were possibly related to households' attempts to adapt to reduced consumption of meat and fish protein sources. Thus, farmers increased intakes of the more readily available and affordable legumes and milk to offset potential meat-fish based protein deficits during the pandemic. In congruence with our observations, PPRC-BIGD (2020) found that the average food expenditure decreased by a larger margin among low-income groups compared to higher-income groups in the Asia Pacific region. There was also a minimal decline in starch food consumption (cereals), while larger declines were experienced in protein-rich foods during Covid-19, which was in agreement with Kang et al. (2021).

The study found that Covid-19 impacted several small-scale farm outcomes, following the IPWRA regression model. The study recorded a reduction in fertilizer use intensity. This was expected because the Covid-19 pandemic negatively impacted input supply and demand globally. Farmers in India reported hardships accessing farm inputs (seeds and fertilizers), as markets were open for limited durations and prices were higher owing to low supplies (Ghosh-Jerath et al., 2022). Similarly, FAO (2020) reported that low agricultural input supplies were already disrupting cropping activities in the East African region. The pesticide transportation costs to the Eastern parts of Africa almost tripled during the early phases of the pandemic, worsening the threat to food security (FAO, 2020), while movement restrictions and import delays affected input supply patterns (Schmidhuber et al., 2020). The negative impact of Covid-19 on the FCS and daily calorific intake was expected due to its negative effects on farm production activities and farm incomes which are likely to reduce farm productivity and access to food. The increases in food product prices coincided with substantial declines in household incomes, particularly for low-income farms, which reduced the diversity of food products consumed, thereby impacting on the daily calorific intake values.

Table 11 presents a synthesized summary of Covid-19 effects for key farm production and food security indicators, focusing on statistical significance, ordinality and direction of change. Across the sample, there was a significant decline in crop area, input (fertilizer and manure) application rates and the FCS. There were significant typology differences in crop area, manure expenditure and the FCS measure. Type 3 farms recorded higher crop areas, relative to type 1 and 2 farms. The higher FCS among type 3 farm households was expected due to several factors including better utilization of farm inputs and the fact that crop cultivation areas did not decline significantly in this farm type. The results point to important geographic differences that may explain farm vulnerability and coping potential to disruptions such as Covid-19 as county differences were significant across all key farm and food security measures that were investigated. The income losses and food price increases due to Covid-19 are likely to disproportionately affect food security for low-income households, partly because they spend large proportions of their income on food items (up to 70 %), while resource-endowed households spend smaller shares of their incomes on food (Laborde et al., 2020). The most important Covid-19 impacts among poor and vulnerable people is caused by loss of on-farm and off-farm income sources (Laborde et al., 2020). The linkage between farm input utilization and household food security outcomes varies between agro-ecological and socio-economic factors, which should be accounted for in future interventions to cope with disruptions like Covid-19.

5. Conclusions and policy recommendations

The study assessed differential impacts of the Covid-19 pandemic on agricultural productivity, farm input use, access to agricultural information and food security of small-scale farmers in different geographical regions and farm types of Kenya. While all farm types experienced challenges related to the Covid-19 pandemic, wealthy farm households experienced lesser disruptions in their agricultural production activities, including harvesting delays, disruptions in off-farm incomes, access to agricultural inputs and farm credit compared to poor farm households. This may be related to their ability to access inputs and needed labour at critical production times compared to the other farmer categories.

The Covid-19 pandemic impacted negatively on agricultural information access, input use patterns, FCS and calorific intake values. It implies, that the generalization of negative impacts and interventions across a broader category commonly referred to as small-scale farmers could mask the farm-type specific impacts, while farmer-type clusters are affected differently depending on their levels of vulnerability because they are not homogeneous. There is a need for a differentiated projection of the effects of future disruptions based on farm categories and targeted interventions. The poorer farmers tend to be more vulnerable and their coping strategies tend to be depletive and largely unsustainable e.g. sale of livestock herds as a coping strategy, could worsen long-term vulnerabilities. Investments aimed at reversing the long-term impacts of Covid-19 should be targeted to the vulnerable small-scale farmers, least able to cope with the shocks caused by the pandemic.

Given the broad application of our results across the developing world and SSA countries, in particular, there is need to improve small-scale food production through input provision mechanisms and strengthening input and output market networks during such a crisis. The study indicated that cropping areas and input use declined for some crops, partly due to weak policy coping mechanisms during the Covid-19 pandemic in Kenya. Evidence shows that farmers coped with Covid-19 food production and consumption challenges, including enhancing their use of locally available livestock manure and dietary adjustments to cope with declines in meat, fish, sugar, oil, and cereal calorific intakes. The SSA governments and development partners should respond to future food system disruptions using policy frameworks that strengthen the local capacity of small-scale farmers to cope with future disruptions in the farming system. Such disruptions are becoming

Table 11
Synthesis of farm system and food security Covid-19 effects.

Farm parameters	Period (main effect)	Typology (main)	Typology*Period (interaction effects)			County (main)	County*Period (interaction)				
			1	2	3		Makueni (*mk*)	Nakuru (*nk*)	Kakamega (*kk*)	Siaya (*sy*)	Bungoma (*bg*)
Improved seed (yes, no)			$X^2 = 2.3$, p = ns				$X^2 = 12.5$, p = 0.013				
Crop area (ha)	***,-	***, $1^c > 2^b > 3^a$	***,-	***,-	ns, −	***, $kk^b > bg^b > sy^b > nk^b > mk^a$	ns,-	*,+	**,-	ns,-	**,-
Fertilizer rate (kgN/ha)	ns, −	ns, $2^a > 3^a > 1^a$	ns, −	ns, −	ns, −	***, $mk^c > nk^c > sy^c > kk^b > bg^a$	ns,+	ns,-	ns,-	ns,-	ns,-
Manure rate (t/ha)	*, +	ns, $3^a > 2^a > 1^a$	ns, −	ns, −	ns, −	*, $nk^b > mk^b > bg^{ab} > sy^{ab} > kk^a$	ns,+	ns,-	**,+	ns,-	ns,+
Manure expenditure (USD ha^{-1})	*,+	*, $2^b > 3^{ab} > 1^a$	ns, +	ns, +	ns,+	***, $kk^c > bg^c > mk^{bc} > nk^{ab}, sy^a$	ns,+	na	ns,+	ns,+	ns,+
FCS	**, −	***, $2^b > 1^b > 3^a$	ns, −	ns, −	ns, −	***, $nk^d > sy^{cd} > mk^{bc} > bg^{ab} > kk^a$	ns,-	ns, −	**, −	ns, −	ns, −

Significance codes are *** (0.001), ** (0.01), * (<0.05), and ns (>0.05). For typology and county main effects, the ordinality of means (ascending) and mean separations (LSD tests) are shown. County names are abridged and italicized, while county/ typology means followed by different letters were significantly different. For Covid-19 phase effects, period main effects, typology*period and county* period interactions are shown as significance values followed by direction of change (increase+ or decrease − during Covid-19 relative to pre-Covid-19 measure). Chi-square tests are included for improved seed use; typology* period and county*period cross-tabulations.

common worldwide and could include other emerging infectious zoonotic diseases, widespread pests and diseases (e.g. locust invasion of SSA in 2019), geopolitical conflicts and climate change. Some possible support mechanisms include:

- Establishment of systems of regional, national, and local food reserves to cope with future supply chain disruptions
- Enhancement of systems for access and dissemination of information using local information access centres and social media dissemination pathways. Such systems could be implemented through locally accessible community information providers
- There is need for rapid responses to safeguard vulnerable farmers from the food systems limitations introduced by disruptions before they cause significant livelihood challenges such as increased poverty levels, food insecurity and malnutrition. Such responses, include support with high-quality inputs and agronomic knowledge.
- Widespread promotion and production of diverse and nutritious foods to enhance adaptation to the inaccessibility of expensive animal or plant-based, calorie-dense foods such as meat, fish and oil during such disruptions.
- With income shocks disproportionately affecting the food security and nutrition of the poor, expansion of social protection measures is crucial for mitigating the short- and long-term impacts of disruptions like Covid-19. Most government Covid-19 assistance is made through formal traditional financing mechanisms, which invariably excludes those in the informal agricultural value chain, who are the majority. Policies need to be targeted to support liquidity and facilitate financial inclusion of vulnerable small-scale farmers and other informal producers.

CRediT authorship contribution statement

James Mutegi: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Ivan Adolwa:** Conceptualization, Data curation, Methodology, Validation, Writing – review & editing. **Abed Kiwia:** Conceptualization, Writing - review & editing. **Samuel Njoroge:** Validation, Writing - review & editing. **Angela Gitonga:** Investigation, Writing – review & editing. **Joses Muthamia:** Investigation, Writing – review & editing. **Eileen Nchanji:** Funding acquisition, Validation, Writing – review & editing. **Franklin Mairura:** Formal analysis, Software, Visualization, Writing – original draft, Writing – review & editing. **Kaushik Majumdar:** Resources, Validation, Writing – review & editing. **Shamie Zingore:** Methodology, Validation, Writing – review & editing. **Thomas Oberthur:** Methodology, Validation, Writing – review & editing. **Mercy Kiremu:** Methodology, Writing – review & editing. **Monica Kansiime:** Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgements

This work was funded by APNI CORE (2020APNI 001) and AGRA/USAID (2020KE005) grant to APNI through the Partnership for Inclusive Agricultural Transformation in Africa (PIATA).. The work was implemented under the technical and scientific leadership of the African Plant Nutrition Institute (APNI). Bill and Melinda Gates Foundation funded publication of this work under the Accelerated Varietal Improvement and Seed Delivery of Legumes and Cereals in Africa (AVISA) grant INV-009649/OPP1198373. We acknowledge the APNI management for supporting the project implementation through generous allocation of staff time. Finally, the authors thank farmers and the county Governments of Siaya, Kakamega, Makueni, Nakuru, Bungoma, for providing responses and data, which are the basis of this publication.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2023.106405.

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