Uptake and impact of climate-smart agriculture on food security, incomes and assets in East Africa

Working Paper No. 251

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Photos:

Abstract

Increasing agricultural productivity and meeting food security needs in the face of climate variability and change in East Africa requires a range of technological, institutional and policy interventions. Climate-smart agriculture (CSA) is increasingly being used as an approach to integrated development. CSA refers to agriculture that sustainably increases agricultural productivity and livelihoods, resilience and adaptive capacity, reduces greenhouse gas emissions where possible, and enhances achievement of national food security and development goals. Since 2011, the CGIAR Research Program on Climate Change and Food Security (CCAFS) has been testing, evaluating and increasing access to and promoting a portfolio of CSA technologies and innovations across Climate-Smart Villages (CSVs) in East Africa. Using quasi-experimental approaches, this paper analyses the uptake and impact of CSA technologies (improved multiple stress-tolerant crop varieties, improved and better adapted livestock breeds and integrated soil and water conservation measures) on livelihood outcomes—food and nutrition security, incomes and asset accumulation, all of which are among the indicators of resilience.

Results show an increase in uptake of CSA technologies and innovations across the CSVs, coupled with improved agronomic and livestock management practices. Farmers adopting multiple stress-tolerant crop varieties and improved small ruminant livestock breeds, for example, had access to more types of food and accumulated more household assets than the non-adopting households. Adoption of improved multiple stress-tolerant crop varieties also increased household dietary diversity by up to 11 percentage points, increased asset index by up to 60 percentage points and more than doubled household income per adult (equivalent $140). Similarly, adoption of improved and better adapted small ruminants increased household dietary diversity scores (HDDS) by up to 10 percentage points and increased asset index by up to 51 percentage points. Although positive, income effects of improved small ruminants were not significant. Impact of soil and water conservation practices is marginal. We, therefore, conclude that adoption of crop and livestock-related CSA technologies and practices has positive and significant impact on food security, asset index and income.

These results indicate that the CSA technologies and practices tested, evaluated and promoted are successful in helping households cope with climate risks and enhancing livelihoods, climate adaptation and resilience of smallholder farmers, and therefore it is important to promote wider uptake of these technologies across East Africa. A key question is how these technologies can be effectively promoted within and beyond the CSVs (scaled up and out). To address this question, the study examined the drivers of adoption of CSA. Group membership, participation in agriculture as the primary occupation, farmer location, gender (female), farmer expectation of occurrence of climate extremes, early receipt of weather forecast, and household wealth were among the factors associated with higher likelihood of adoption of CSA technologies and innovations. Culture, experiences and micro-climate were also important in influencing farmer's choices of CSA technologies and practices, underscoring the importance of participatory action learning approaches that take local knowledge into consideration, for enhancing adaptive capacity of the farmers and their communities. Thus, continuous learning through on-farm demonstrations, farmer fairs, and exchange visits are

very important in accelerating adoption of CSA technologies and innovations with potential to benefit a large number of smallholder farmers. In addition, there is need to evaluate local conditions in a participatory manner before a technology is replicated in areas exhibiting similar biophysical and socio-economic characteristics.

Keywords

Climate-smart agriculture; improved multiple stress-tolerant crops; improved small ruminants; adoption; household income; food and nutrition security; assets.

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Contents

Acronyms

ASF	Animal source food
ATT	Average treatment effects
CBOs	Community-based organizations
CIAT	International Center for Tropical Agriculture
CIMMYT	International Maize and Wheat Improvement Center
CIP	International Potato Center
CSA	Climate-smart agriculture
CSVs	Climate-Smart Villages
ESR	Endogenous Switching Regression
FOKO	Friends of Katuk Odeyo
GHG	Greenhouse gas
HDDS	Household dietary diversity score
HODFA	Hoima District Farmers Association
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IITA	International Institute of Tropical Agriculture
ILRI	International Livestock Research Institute
IPCC	Intergovernmental Panel on Climate Change
KALRO	Kenya Agricultural and Livestock Research Organization
KBM	Kernel-based matching
KIIs	Key informant interviews
KMD	Kenya Meteorological Department
MoALF	Ministry of Agriculture Livestock and Fisheries
NARO	National Agricultural Research Organization
NECODEP	North-East Community Development Programme
PAR	Participatory Action Research
PSM	Propensity Score Matching
NNM	Nearest Neighbour Matching
ROSCA	Rotating Savings and Credit Association
TARI	Tanzania Agricultural Research Institute
TMA	Tanzania Meteorological Agency

1. Introduction

Smallholder farmers in East Africa are experiencing increasing livelihood challenges in this century. These challenges are attributed to increasing scarcity of agricultural land due to population growth, steep rises in food prices, land degradation, deteriorating soil fertility and associated declining crop yields, poor market access and, in some cases, unclear land tenure systems and property rights negatively influence application of technologies and investment in agriculture (Nelson et al. 2010, Yamano and Kijima 2011). Consequently, poverty and food insecurity are increasing (Thornton et al. 2011). Climate change compounds these challenges, with the region witnessing changing climatic conditions characterized by warmer temperatures, changing rainfall patterns and increased frequency and severity of extreme weather conditions and droughts (IPCC 2007, Wheeler and Von Braun 2013). Expected consequences and impacts of these changes include shortened and disrupted crop growing seasons, reduction in area suitable for agriculture and declining agricultural productivity (Connolly-Boutin and Smit 2016). These impacts could have devastating effects on food and nutrition security, and livelihoods of the rural poor, especially in East Africa, where about 80% of the population lives in rural areas and depends either directly or indirectly on agriculture.

In the past, local communities in East Africa employed diverse coping mechanisms and adaptation strategies to reduce or minimize risks from recurrent weather extremes such as droughts and floods. The approaches include migration, income diversification and use of appropriate technology (Babatunde and Qaim 2010, Karamba et al. 2011, Burney and Naylor 2012). More often, however, rural households in the region rely on indigenous knowledge and some degree of trial and error to cushion themselves from climate extremes and change. The strategies often lack complete information on the precise nature of emerging climate extremes and climate change-related challenges, as well as the required climate-smart technologies to respond effectively, build resilience, and enhance the adaptive capacity of resource-poor smallholder rural farming communities. As a result, their responses may, thus, be inadequate, less effective and unsustainable to the emerging climate change challenge. Resilience to climate change and building adaptive capacity require a complex interplay of asset base, access to knowledge and information, an enabling policy framework and institutional environment, innovation, flexible forward-looking decision-making and governance at the local level (Jones et al. 2010). Availability of key assets allows individuals, communities or regions to respond to evolving climate-related hazards and circumstances. An enabling policy framework and appropriate institutional environment allow fair access and entitlement to the key assets. An enabling environment for experimentation and innovation is key, in order to derive niche solutions to take advantage of emerging opportunities. In addition, there must be a system to collect, process and disseminate information and knowledge to support resilience building efforts and adaptation activities. The system must be flexible enough to be able to anticipate, incorporate and respond promptly to changes within its governance structure and planning.

Smallholder farmers with low adaptive capacity living in fragile agroecosystems lack resilience to climate change, and would be unlikely to undertake appropriate adaptation measures. Thus, it is important to mobilize and support these resource poor communities to build their asset base and local institutions for collective action in order to develop and strengthen resilience, climate change adaptation and mitigation. Research institutions need to be mobilized to generate knowledge and information consistent with local conditions and develop context specific climate-smart technologies and practices. These research products need to be disseminated to smallholder farmers for scaled up implementation and to policy makers for evidence-based decision-making.

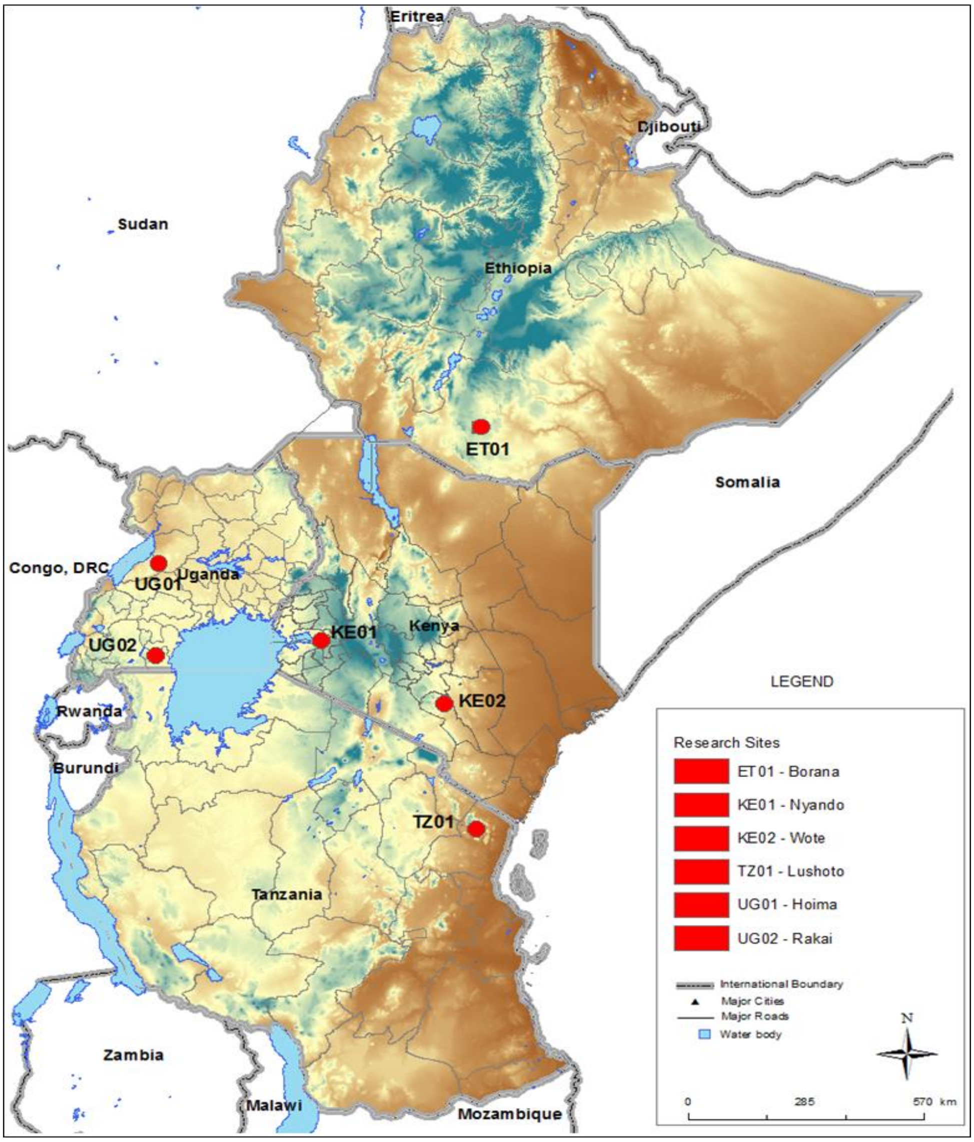
In order to generate the evidence on the efficacy of climate-smart options, the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) initiated the Climate-Smart Villages (CSVs) Research for Development (R4D) in line with the above approaches to test, through participatory methods, climate-smart technological and institutional options for dealing with climate change in agriculture, with the aim of scaling -out and -up the appropriate options and drawing out lessons for policymakers from local to global levels (Aggarwal et al. 2018). The ultimate goal is to build the resilience and adaptive capacity of smallholder farmers and enable them to achieve sustainable food and nutritional security, and socio-economic progress in the face of climate change, and where possible contribute towards climate change mitigation through carbon capture and storage and t reduction of greenhouse gas (GHG) emissions.

1.1 Climate-Smart Villages in East Africa

CSVs are clusters of villages that focus on climate change hotspots across a wide range of agro-ecological zones with different farmers' typologies, climate risks and vulnerabilities allowing comparison, learning, extrapolation and climate analogue analysis. The CSVs represent areas that are becoming both drier and wetter, and are focal locations where participatory action research (PAR) efforts are expected to generate results that can be applied and adapted to other similar regions worldwide. In such villages, researchers from national and international institutions, local partners and farmers collaborate to test a portfolio of CSA technologies, practices and innovations, with the aim of identifying and implementing locally appropriate ones.

In East Africa, CCAFS started piloting the CSVs approach in 2012 in six sites—Lushoto (Tanzania), Wote and Nyando (Kenya), Hoima and Rakai (Uganda), and Borana (Ethiopia) (Figure 1). These sites are characterized by widespread environmental, socio-economic and climate risks and vulnerabilities including soil erosion and land degradation, declining soil fertility, deforestation, frequent fluctuating precipitation patterns, water stress, droughts and in some areas floods, high incidence of pests and diseases, high population growth rates and the associated decline in farm sizes and pasture, high rates of poverty, low farm labour productivity and food insecurity (Kristjanson et al. 2012, Förch et al. 2013, Recha et al. 2017). Every CSV has a portfolio of CSA activities and innovations. These include Weather-Smart (seasonal weather forecast and agro-advisory services); Water-Smart (rain water harvesting and soil erosion control); Carbon-Smart (agroforestry, trees for fodder and forage, fuel wood and fruit trees, and composting manure); Crop-Smart (improved and drought-tolerant cereals, leguminous, tuber and fodder crops, and improved agronomic practices); Livestock-Smart (improved small ruminant livestock, poultry systems and management practices, community para-veterinary services to tackle emerging disease pests and parasites), and Knowledge-Smart (smart farms, collective action groups and farmer-to-farmer learning). The overarching goal is to stimulate actions that would enable the communities and households to respond to climate extremes and change so as to reduce hunger, ensure food security and enhance household incomes (Kinyangi et al. 2015).

Figure 1. Climate-Smart villages in East Africa



To enhance their resilience and capacity to cope with or adapt to climate variabilities and change-related challenges, farmers within the CSVs in East Africa work in pre-existing community groups that were and still are the essential fabrics of the cultural and traditional social networks and safety nets organized to address various socio-cultural and economic challenges of the communities. For example, some were formed for the purposes of pooling financial resources through Rotating Savings and Credit Association (ROSCA) schemes and pooling farm labour. Others were mainly for such social reasons as support to orphans, widows and other vulnerable groups. These community groups provide an excellent platform for innovative partnerships for new knowledge and skills, and for building capacity of local farmers to change farming practices and to adopt new climate-smart crops and livestock. Through the groups, farmers can easily be mobilized to introduce new technology and practices, as well as build capacity, and in return they can provide opportunities to establish individual and community owned demonstration smart farms, share useful indigenous knowledge and monitor progress. The groups also provide effective avenues for members to pool financial resources for savings, administer innovation funds, provide farm labour and enhance efficient delivery of extension services and farm inputs, especially in East African countries where extension services are not centralized. We briefly describe each of the CSVs in East Africa, including key partners:

Lushoto in Tanzania: - Lushoto lies in the north east of Tanzania, with hilly landscapes intersected with very steep slopes. Lushoto is in a mid to high altitude ecology with two seasons of rainfall (March–May and October–December). The altitude ranges from 1,200 to 2,250 m above sea level. Annual temperature range is 11-25ºC. Average annual rainfall is variable, ranging from 900 to 1,300 mm. The long-term daily rainfall data (from 1922 to 2012) for Lushoto from the Tanzania Meteorological Agency (TMA) shows a decreasing precipitation trend in the region (Recha et al. 2015). Lushoto's soil type is Umbric Acrisols. Lushoto is characterized by two agro-climatic zones - humid warm and humid cold zones. The farming system is mixed crop-livestock, with intensive farming in the higher altitude areas and agro-pastoral systems in lower altitude areas. It is one of the most densely populated rural areas in Tanzania (over 134 persons per km^2). Land holdings are relatively small, with an average land size of two acres per household. The area is a global hotspot for biodiversity. Agriculture is the main livelihood source for the majority of Lushoto's households, and crops grown include maize, potatoes and beans. The main challenges for agriculture include small and declining land size, soil erosion and land degradation due to the steep slopes, and declining soil fertility, soil organic matter and carbon stock. Climate-related risks include rainfall variability, shifting seasons with longer dry spells, and an upsurge of pests and diseases for crops and livestock. There has also been a failure to improve environmental services due to lack of an enabling policy and institutional environment.

Key partners in Lushoto include Tanzania Agricultural Research Institute (TARI), Lushoto District Council, Sokoine University of Agriculture, TMA, Tanzania Forestry Research Institute, community based organizations (CBOs), and Tanzania Ministry of Agriculture and Livestock Development.

Hoima and Rakai in Uganda: - Hoima is located in western Uganda to the east of Lake Albert. The landscape is characterized by hills and midlands, with an altitude ranging from 1,200 to 1,600 m above sea level. Most of the area is relatively flat and low lying in its topography alternating with broad hills. Annual temperature range is 16-30ºC. Average annual rainfall is about 1,400 mm, spread over two seasons (April–May and August–November). Precipitation patterns are highly variable, both within and between seasons. The average monthly rainfall and number of rainy days show a decreasing trend, especially during the critical months of crop growth (April–June and September–November) (Recha et al. 2016). Hoima has three sub-agro-ecological zones: western mid altitude, Semliki river flatland, and moist northern farmlands. The soils are Ferralsols and Fluvisols, and the vegetation is mainly savannah with short and tall grasses and shrubs.

Agriculture is the main economic activity, supporting about 90% of households in Hoima. Other livelihood activities include fish farming and beekeeping. Agroforestry is practiced in the highlands, while coffee and tea are the main crops for the mid-hill areas. Small-scale mixed farming, or agro-pastoralism, is practiced along Lake Albert. The main crops grown in the low lands include maize, beans, cassava sweet potatoes, finger millet, sorghum and bananas. Cattle, sheep, goats, pigs, and poultry are the most common livestock types among households in the highlands and lowlands areas of Hoima. The main challenges for agriculture include declining soil fertility and widespread erosion, affecting about 20% of the landscape. Climate-related risks include rising temperatures, increasing rainfall variability, increased incidence of pests and disease affecting both crop and livestock productivity, and resulting in declining food security

Rakai is located in southern Uganda, west of Lake Victoria, with an altitude of 1,280 m above sea level. The temperature range is 15–26ºC. Rainfall pattern is bimodal, spread over two growing seasons: March–May and September–December. Annual rainfall ranges from less than 1,000 mm in the west to over 1,400 mm along Lake Victoria. The main soil types are Nitisols and Leptosols, while the vegetation includes forest and woodland, savannah shrub and grasslands, and wetlands. Rakai has mixed farming systems, with annual smallholder crop farming along the lake, perennial mixed coffee agroforestry in the central region and smallholder agro-pastoralism in western areas. Main staple crops grown include maize, banana, cassava, beans, potato and sweet potato, while cash crops include coffee, tobacco, and sugarcane. However, the communities rely more on perennials such as bananas and cassava. The main challenges for agriculture include decreasing precipitation with poor distribution, gradually reduced river flows, as well as water and heat stress. Rakai is also heavily grazed due to migration of livestock from Tanzania. Deforestation as a result of charcoal production and over-dependence on fuel wood also represent significant challenges, all of which contribute to further environmental degradation.

Key partners in Hoima and Rakai include National Agricultural Research Organization (NARO), CIAT, International Institute of Tropical Agriculture (IITA), International Potato Center (CIP), the district agricultural offices, HODFA and local organizations such as farmer groups in CBOs.

Borana in Ethiopia: Borana in southern Ethiopia is a typically semi-arid ecosystem, with an altitude ranging from 1,200 to 1,400 m above sea level. Annual temperature range is 18-31ºC. Rainfall pattern is bimodal and distributed over two growing seasons: March–May and September–November. Annual rainfall ranges from 500 to 600 mm. The main soil type is Cambisols along with Luvisols in flat areas and valley bottom landscapes. Borana is characterized by four types of vegetation: evergreen and semi-evergreen bush land and thickets, rangelands dominated by Acacia and Commiphora trees, and dwarf shrub grassland.

The Borana people are mainly pastoralists, with beef cattle and goats dominating the agricultural landscape, although subsistence crop production (sorghum, maize, and beans) and poultry farming have been introduced more recently. Climate-related risks include more frequent droughts, with increased rainfall variability, water and heat stress. In the last 10 years, for example, Borana has experienced five consecutive droughts. Other environmental challenges include land degradation and loss of soil fertility. Traditionally, water and pasture scarcity in this rangeland has been managed through cultural institutions structured around clusters of hand-dug deep wells. These have since been weakened by climate and other changes and exacerbated by frequent dry spells.

Key partners in Borana include Managing Risk for Improved Livelihood (MARIL), National Meteorological Agency (NMA), Yabello Pastoral and Dryland Agriculture Research Centre (part of Oromia Agricultural Research Station); Addis Ababa University; and Yabello district local government (Department of Environmental Management).

Nyando and Wote in Kenya: - Nyando Basin in western Kenya is a rich agricultural flood plain near Lake Victoria. Altitude ranges from 1,100 m in areas near the lake to 2,500 m above sea level in the headwaters. The temperature range is 15-32ºC. The climate is humid to sub-humid with average annual rainfall of 900 to 1,200 mm, distributed in a bimodal pattern: March–May and September–November (Verchot et al. 2007, Tobella 2009). The soil types of Nyando are Cambisols and Luvisols. Vegetation is mainly shrubs and grasses. About 40% of the Nyando landscape is degraded due to flooding.

Agriculture remains a major source of livelihood for households in Nyando, providing food and a significant source of income. The farming system is largely subsistence mixed with rainfed crop-livestock systems. The main food crops include beans, maize, green gram, pigeon pea, cowpea and sweet potato. Other crops include sorghum, finger millet, tomato, kale, cassava and banana. Livestock includes cattle, small ruminants, fish and poultry.

Climate-related risks include frequent droughts, increasingly unpredictable rainfall patterns, flooding in the lower basin during intense seasonal rainfall events, water and heat stress, all of which are indications of a changing climate (Kinyangi et al. 2015). Other environmental challenges include land degradation, soil erosion, and declining soil fertility, organic matter and carbon stocks. These challenges are compounded by high poverty rates and low farm labour productivity, while the rising population has resulted in less land for both cultivation and pasture.

Key partners in Nyando include VI Agroforestry, ILRI, KALRO (Kibos) and community-based organizations (CBOs) (Friends of Katuk Odeyo (FOKO), North-East Community Development Programme (NECODEP), Kapsokale), World Neighbours, County Government of Kisumu and Kericho, Magos Farm Enterprises and Honey Care Africa.

Wote is located in eastern Kenya, with a climate characterized as semi-arid. Altitude ranges from 900 to 1,000 m above sea level, with a temperature range of 18-35ºC. Rainfall pattern is bimodal: March-April-May (MAM) and October-November-December (OND). Annual rainfall ranges from about 480 to 800 mm. MAM rains are becoming more and more poorly distributed, resulting in shorter crop growing periods and affecting agricultural productivity, food security and livelihoods of smallholder farmers. The dominant soil types are Ferralsols, Lixisols, and Arenosols. The area is dominated by gently undulating landscapes with long gentle slopes.

The farming system in Wote is subsistence mixed rainfed crop-livestock. The main food crops that are grown are maize, cowpea and pigeon pea. Other crops include beans, sorghum, green gram, and pearl millet. Livestock includes cattle, goats and poultry. Major sources of income for the smallholder community include beekeeping, small-scale trade, livestock keeping and fruit farming. Climate-related risks and environmental challenges include periodic flooding that occurs due to high intensity precipitation falling within short time periods during the rainy season. This results in reduced infiltration, fluctuating and unpredictable rainfall patterns, especially in the short rainy seasons, water and heat stress, increased incidence of pests and disease, soil erosion, loss of soil fertility and productivity. Indeed, 25% of the landscape is extremely degraded and requires intensive climate-smart landscape restoration measures. The risks and environmental challenges have negative impacts on agricultural production, affecting the resilience and adaptive capacity of smallholder farmers to climate variability and change.

Key partners in Wote include KALRO (Katumani), Kenya National Federation of Agricultural Producers (KENFAP), ICRISAT, and Makueni County.

1.2 CSA technologies and innovations in East Africa CSVs

Various CSA technologies and innovations have been implemented in the East Africa CSVs since 2011. The portfolio of technologies and innovations differ across CSVs based on farming systems, agro-ecosystems, livelihoods, climate and environment-related risk factors. The main interventions are summarized below:

Institutional innovations for climate risk management

To enhance collective action, the communities in the CSVs have been mobilized to expand their social groups as institutional platforms for agricultural learning, delivery of farmer advisory services and agricultural inputs, mobilizing financial resources for loans and mobilizing farm labour especially for the construction of soil and water conservation structures. These institutional platforms were also used for setting up demonstration farms as agricultural knowledge hubs.

In Lushoto-Tanzania, three CBOs (Kwamaga, Mbukwa and Yaboga) were established in 2012 and were transformed into village savings and credit cooperative societies (SACCOs) in 2014. The SACCOs cover 29 villages, with a direct membership of 1,089 households and 6,500 individual beneficiaries of which 55% are women. The members have mobilized resources to create an innovation fund amounting to $35 000 where they can receive loans for agricultural investments. The SACCOs play an important role in improving access to farm inputs in Lushoto, mobilizing labour for construction of soil and water conservation structures and establishing tree nurseries.

In Hoima-Uganda, two CBOs (Bagonza-Kukora and Kyabigambire) were formed in 2013, initially covering only 7 villages. Through capacity building, the CBOs expanded to cover 15 villages, with a membership of 720 households and 4,300 individual beneficiaries, of which 50% are women over a period of three years (by 2016). Similar to Lushoto, the groups in Hoima have pooled an innovation fund of $41 000 for loaning to members for on-farm investments. The Hoima CBOs have been useful avenues for disseminating CSA such as resilient varieties of root crops including cassava and sweet potato, and of cereals (maize, millet, sorghum) which have been adopted by about 97% of the households.

In Borana-Ethiopia, two collective action groups were established in 2011. With subsequent efforts to build capacity of the groups, membership has grown from 40 to 450 households (2,700 beneficiaries in total) in 2015, half of which are women. The groups have pooled together an innovation fund of USD $4 000 for lending to members for investment to improve livestock production and support diversification into dryland crops. The groups have also implemented technologies that enhanced rangeland rehabilitation.

In Nyando-Kenya, communities have organized themselves into three CBOs: FOKO, NECODEP and Kapsokale. Together, these three CBOs are made up of 58 self-help groups from 106 villages, covering 2,500 households (about 13,000 individuals). Women account for 80% of the membership of the self-help groups. The CBOs pooled their financial resources together from $14 000 in 2011 to $95 000 in 2015 for an innovation fund to provide credit to members for on-farm agricultural investment, as well as other livelihood and resilience building activities. About 90% of the farmers have borrowed from the fund to purchase improved inputs, buy food, pay school fees and for small scale trade such as basket weaving and grocery shops.

In addition, the CBOs have set up smart-farm demonstrations that showcase greenhouse farming and solar-drip irrigation involving horticultural crops, legumes, fruit crop and fodder production, fisheries and apiary. They also undertake seed multiplication for the community in the open field demonstration plots, and farmers receive training via field days and trade fairs through the CBOs. The CBOs have set up local input supply shops to enhance access to high quality inputs at affordable prices. This has reduced the number of farmers using non-certified seeds by up to 50%. The CBOs, in partnership with Kenya Meteorological Department (KMD) and Maseno University have facilitated access to climate information, benefiting about 70% of farmers to make on-farm decisions.

In Wote-Kenya, two CBOs (Sinai-Kikeneani and Kikumini-Muvau) were formed in 2014 with an initial membership of 140 households. This has grown to 620 households consisting of 3,700 individuals as of end of 2016. About 70% of the membership of these CBOs is made up of women. The CBOs have pooled approximately $39 000 into an innovation fund, from which members borrow for investment in agricultural activities. The CBOs have also been useful as platforms for dissemination of CSA technologies and innovations, mainly dryland cereals and legumes, and soil and water conservation measures.

Smart farms for adaptation learning

In order to address seasonal rainfall variability and accelerate learning, farmers in Nyando are using the smart farm concept. A smart farm comprises of a greenhouse (on up to a quarter of a hectare), combined with drip irrigation from a mini-earth dam with the advantage of saving water. The greenhouse is free from flooding and drought, and offers better control of pests and diseases. Because of the regular production cycle, the harvest can be better timed for local markets. The smart farms also serve as community demonstration and learning hubs to showcase appropriate and successful CSA practices such as water conservation through the construction of mini earth dams with a minimum capacity of 100,000 litres of water and solar pumps. Other smart farm technologies include soil conservation, horticultural crop seed bulking and fodder production. Nyando CSVs, for example have four smart farms spread across four villages. The smart farms are mainly managed by women and youth groups. Some smart farms have also embraced fish farming (aquaculture). For example, Kamula youth group has constructed a second earth dam with a capacity of 100,000 liters of water and stocks it with 1,000 fingerlings per season, producing a steady supply of fish for the community to diversify its diet, supply the nearby market and increase their incomes. The group also produces fodder crops such as Boma Rhodes and Napier grass, and manages five colonized bee hives producing up to 45 kgs of honey per hive three times a year.

Building resilience through multiple stress tolerant crop varieties and crop diversification

Improved crop varieties that are early maturing, with tolerance to drought and floods, tolerance to pests, and resistant to diseases, have been introduced and tested in the CSVs. In Lushoto, and Hoima, working in collaboration with CIAT Pan-Africa Bean Research Alliance (PABRA), over 1,800 households are planting improved high-yielding drought-tolerant bean varieties. These include bean varieties that are resistant to emerging pests and diseases, following satisfactory preliminary performance to evaluate these improved varieties at scale on over 750 hectares of land, (Mukankusi et al. 2015). Similarly, in partnership with CIP and IITA, early maturing cassava, and improved varieties of Irish and sweet potato that are resistant to diseases have been evaluated with farmers in Lushoto to enhance productivity and resilience of smallholder farmers. In particular, an Irish potato variety that is resistant to late blight has been introduced in Lushoto by CIP and TARI. Other crop-related CSA technologies piloted in Lushoto include early maturing and pest tolerant varieties of maize in partnership with CIMMYT. In Hoima, resilient and high-yielding sweet potato and cassava varieties have been introduced in partnership with NARO, CIP, and IITA.

In Nyando and Wote, over 3,100 households are using at least ten CSA practices on over 1,300 hectares of land. These include use of new early maturing and water stress tolerant crop varieties for maize, sorghum, beans, and cowpeas, planting new types of crops, and integrated with improved agronomic practices such as timely land preparation and planting based on seasonal weather forecast, appropriate spacing, and weed management, integrated pest management, crop disease surveillance and control, crop rotation, use of intercrop innovations and appropriate use of fertilizers. Most households are diversifying into new crops to increase productivity and reduce chances of complete crop failure. New crops such as pigeon peas and green grams have been planted alongside traditional legumes such as beans and cowpeas. Pigeon pea has the advantage of withstanding drought as well as water-logging, while the leaves can be harvested and used as fodder for small ruminants. Other improved crop varieties that have been introduced include cassava which is resistant to mosaic virus, sweet potatoes which are adapted to low moisture, tissue culture bananas which are resistant to bacterial wilt, and mangoes and pawpaw trees whose fruits are harvested for home consumption as well as for the market. In Wote, farmers are planting dryland cereal crops such as maize, sorghum and millet, and dryland legumes such as green grams and cowpeas. The cereals and legumes are planted in one season, while horticultural crops and fruit trees are planted throughout the year in areas near major water sources where micro-irrigation is feasible.

Improving incomes and climate resilience through improved small ruminants

Working with ILRI, Vi Agroforestry, Kisumu and Kericho County Departments of Agriculture, Livestock and Fisheries, and CBOs, over 2,500 households in Nyando have been trained on improved livestock breeding and management. The focus has been on small ruminants (sheep and goats) and poultry which are less labour intensive and with greater control over the returns by women as compared to cattle. Breeding bucks and rams of Galla goats and Red Maasai sheep were introduced into the villages in 2012 and part of 2013 to upgrade the indigenous (small east African) breeds. In addition, farmers are trained on improved husbandry practices for Galla goats and Red Maasai sheep.

Galla goats are better adapted to drylands and mature almost six months earlier than the local breeds. Moreover, they have good milking ability and have the advantage of being docile and easy to handle. Female Galla goats have a longer productive life and can breed for as long as 10 years. Red Maasai sheep are bred for meat and are popular for fast growth and maturity, resistance to internal parasites, and tolerance to trypanosomes, drought and heat stress. Cross breeds of the Galla goats and the Red Maasai sheep with their local counterparts mature faster and attract almost three times the price of the local breeds in the local markets. A mature Galla goat, for example, can fetch as high as $80-120 while a mature East African goat fetches only about $25-30. It is estimated that as a result of cross-breeding, 2,500 cross-bred sheep and 15,000 goats are added to the Nyando flock annually. About one-third of the current population of sheep and goats in the villages are improved crosses.

Soil and water conservation through agroforestry

About 5,400 households across the CSVs in East Africa have integrated soil and water conservation and agroforestry into their farms, covering at least 2,700 hectares of land. Agroforestry is important for food (fruit trees), fuel, fodder, finance and improved soil fertility. Other soil and water conservation methods which have been integrated in farming include construction of terraces with contoured grass strips to prevent large scale loss of top soil, enhance water retention and provide fodder. To cope with the rising demand for tree seedlings farmers have been encouraged and supported to establish tree nurseries. A total of 63 tree nurseries have been established in Nyando, Lushoto, and Hoima with a capacity to produce 450,000 high quality tree seedlings per season. Farmers have identified priority areas that require urgent tree cover, and these include open areas, farmland and road sides. The selection of tree species is based on farmers' needs, and the preferred tree species include *Pinus patula* and *Eucalyptus grandis* (for wood); *Grevillea robusta* (for farm boundaries and contours); and *Casuarina cuninghamiana* (for wind breaks and along roadsides). Preferred fruit trees include improved varieties of avocadoes, plums and apples in Lushoto; mangoes (*Boribo, Bire* and *Tommy Artkins*) and pawpaw (*Yellow fleshed papaya*) in Hoima; and pawpaw and passion fruit in Nyando. In addition, over 70% of the households in Wote are integrating soil and water conservation measures and agroforestry into their farming practices.

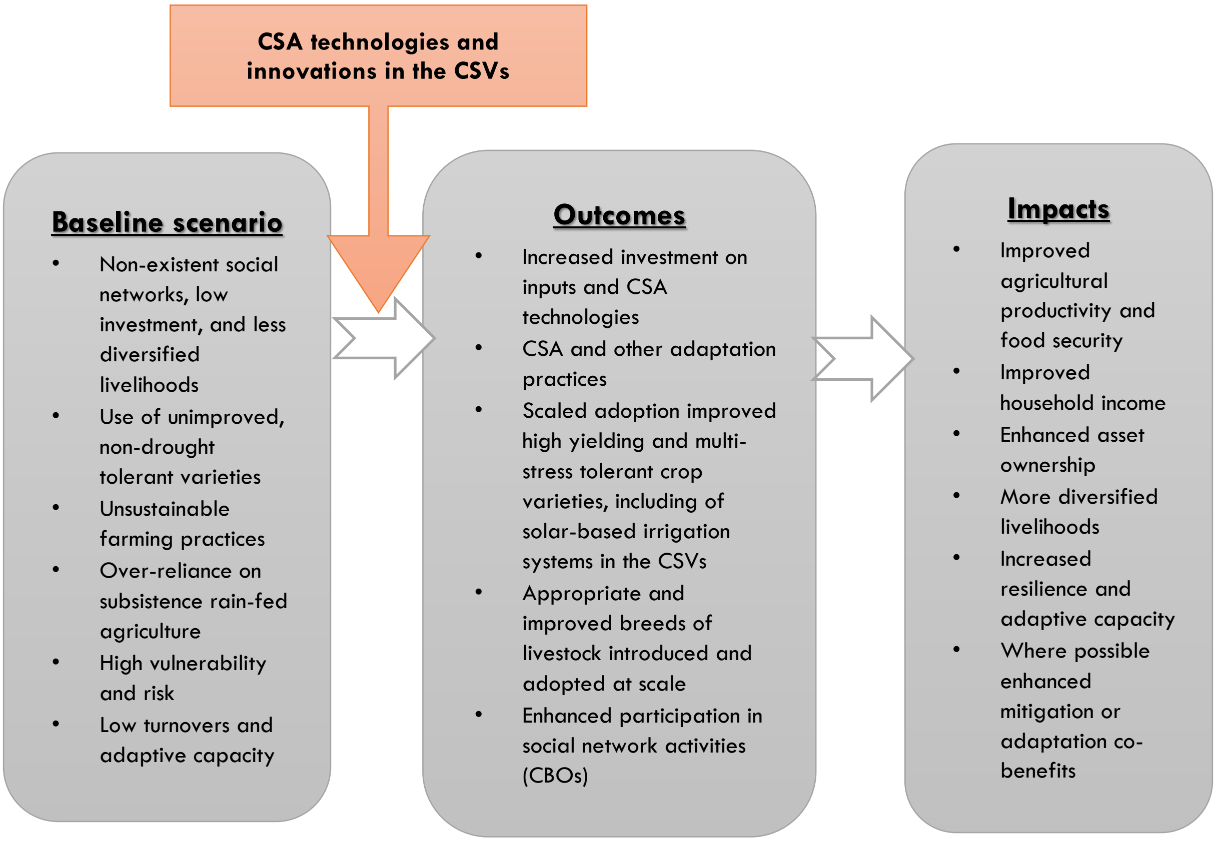
Sharing climate information to enhance climate risk management

For farmers to make decisions on what crops and when to plant and/or harvest, reliable climate information is important. In Lushoto, CCAFS is working with indigenous knowledge weather forecasting teams and the TMA to generate weather forecasts which are shared with farmers through mobile phone short message services. In Nyando, CCAFS is working with Maseno University and KMD to share weather forecasts with farmers. In Uganda, NARO engages farmers to collect weather data on their own farms and submit for expert analysis. The appropriate information for farmers is then packaged and shared with them through the CBOs.

1.3 Envisioned impact pathways

The CSA interventions and institutional innovations being implemented by partners and farmers in the CSVs are expected to have varied outcomes and impacts on communities and households. At the outcome level, farmers are expected to increasingly adopt CSA technologies and practices. These are expected to present farmers with opportunities to improve and diversify their livelihoods, as well as enhance their resilience and adaptive capacities to climate variabilities and change (see Figure 2).

Figure 2. Impact pathways of CSA technologies and innovations



Adoption of CSA practices and innovations can improve household livelihood outcomes, either directly or indirectly (Becerril and Abdulahi 2010, Moyo et al. 2007). Direct effects could include crop and livestock productivity gains and reduced cost of production, leading to improved food and nutrition security, and household income and wealth indicators. Indirect effects could include increased supply of food staples, leading to improved access to food through the markets due to affordability. Moreover, increased productivity may enhance demand for farm labour, resulting into improved earnings among the poor households who dominate the supply of farm labour. Overall, adoption of CSA technologies and practices is an important step towards achieving food and nutritional security (Langyintuo et al. 2008), improving household welfare (Mendola 2007), and for farmers' enhanced resilience and adaptive capacity to climate change and variability, while also contributing where possible to climate change mitigation.

For the CSVs, it is envisioned that adoption of CSA technologies and innovations such as drought-tolerant crops, coupled with sustainable agronomic practices, would boost production of staple food crops even with the changing climate and bridge the hunger gap. Surplus output of these crops could be marketed to enhance household income, and provide other opportunities for investments. The same applies to climate change adaptation actions and interventions such as agroforestry and composting that build soil organic matter and carbon stock with positive consequences for soil health and crop yields. Improved livestock breeds with faster growth coupled with improved management practices through training and support from extension officers is expected to improve the availability of animal source proteins to the households and enhance food and nutritional security. It also has the potential of reducing GHG emission intensity through fewer but more productive livestock. In addition, achieving climate change mitigation in the livestock sector depends on improvement in feeding practices (better pastures, new types of feed, and more grains) and improved ways of handling livestock by-products such as manure. These strategies are based on sustainable intensification: producing more livestock protein with fewer resources; and storing carbon in the land. When the livestock and/or their products are sold, household incomes and resilience, as well as adaptive capacity are improved. Moreover, household participation in collective action initiatives and groups enhances their access to credit facilities often offered by such outfits. Credit acquired from these sources can be invested back in agriculture and other income generating ventures with positive implications for household food security and income. Interesting gender effects are also likely to emerge from these initiatives. For example, women form about 80% of active membership of the community groups through which CSA interventions are channeled. Moreover, small ruminants and poultry often tend to fall under the domain of women in East Africa, and therefore improvement in returns from these enterprises will likely accrue more to women members of the households, making the system more gender inclusive.

In Table 1 we summarize the number of households taking up different CSA technologies and practices across the CSVs of East Africa. It is clearly evident from Table 1 that the CSVs approach has yielded tangible changes among the smallholders, with the uptake of CSA technologies and innovations increasing over the years (Recha et al. 2017, Bonilla-Findji et al. 2017).

Table 1. Households taking up different CSA technologies

Technology	Number of households directly implementing/benefitting					
	Nyando	Wote	Lushoto	Hoima	Rakai	Total
Improved small ruminant livestock	1900	-	-	-	-	1900
Multiple stress tolerant crops	2350	750	1600	2200	-	6900
Intercropping	2350	750	1600	2200	-	6900
Tree planting	800	400	650	700	-	2550
Water harvesting	150	350	300	100	-	900
Use of weather forecast	2350	750	1600	2200	-	6900
Capacity building	2350	750	1600	2200	-	6900
Informal group/individual loans	2350	750	1600	2200	-	6900

Source: Bonilla-Findji et al. 2017

These are implemented alongside other sustainable agricultural practices such as optimized use of organic and inorganic fertilizers, integrated soil and water conservation, optimized planting time and density, planting in row, and disease, pest and weed management. While monitoring and evaluation data from Nyando and Lushoto indicate that these CSV activities may have led to improved livelihoods (e.g. the proportion of food secure households improved from 1.4% to 9.7% and 4.3% to 22% in Nyando and Lushoto, respectively, between 2011 and 2016), the broader impacts on food security, resilience and adaptive capacity of the smallholder communities in these CSVs have not been quantified. This study examines the uptake and impacts of the CSA technologies and innovations on three household welfare indicators using the Nyando CSVs as a case study: household food and nutritional security, incomes and asset accumulation all of which are among the indicators of resilience. Such quantification of adoption and impacts is important for identifying the viable components for replication and scaling up. It is also important to generate empirical evidence on determinants of adoption of CSA technologies and practices, impacts of adoption be it of a single or a combination of multiple CSA technologies and practices, and use the evidence to develop a knowledge framework that matches different CSA technologies with biophysical, socio-economic and socio-cultural characteristics of the different agro-ecological zones in East Africa. Nyando CSV was selected in this test case study because almost all the CSA technologies and innovations described in section 1.2 have been implemented at this CSV.

Previous studies on adoption and impacts of different improved agricultural technologies have yielded mixed results. Improved pigeon pea, legume and groundnut technologies in Tanzania, Ethiopia and Uganda were found to improve household consumption expenditures and reduce poverty (see Amare et al. 2012, Asfaw et al. 2012, Kassie et al. 2011). Adoption of improved seed varieties has also been found to improve yields and gross farm returns (Kiiza et al. 2012). Other studies, however, have observed that the improved technologies yield positive welfare effects on higher income households but negative effects on poor households (Hossain et al. 2003, Gabre-Madhin and Hagblade 2004). In some cases, such technologies have only had modest impacts on household welfare (Bourdillon et al. 2003). We recognize the fact that CSA technologies or adaptation practices in general can only yield results when adopted and implemented properly. Adoption itself may be driven or constrained by farmer or farm-specific factors, access to information, access to the technology, human capital and institutional factors (Amare et al. 2012, Asfaw et al. 2012). However, proper implementation of the adopted technology is often dependent on the information available to the farm households and the level of resources required.

In Nyando, farmers are mainly small scale and largely depend on agriculture for food and income. These households are resource-constrained and highly vulnerable to the vagaries of weather, being mainly reliant on rain-fed agriculture. Thus, working within the framework of CSVs, the farmers are likely to benefit from tested CSA technologies to enhance their resilience and livelihoods to cope with climate variability and adapt to climate change. The aim of this study is two-fold. First, to examine the drivers of uptake of CSA technologies and innovations. Second, to evaluate the impact of the adopted CSA technologies and innovations on household welfare indicators (resilience outcomes)—food and nutrition security (dietary diversity score), household income and household assets. This is especially important for selecting CSA technologies to scale up, for review of implementation approaches, and to gauge the contribution of the CSA technologies and innovations to building resilience and adaptive capacity of smallholder farmers. Using household data and controlling for possible endogeneity, we estimate the drivers of adoption of CSA technologies that are being tested and promoted within the Nyando CSVs, and the impact of the different technologies on the various household welfare and resilience indicators.

2. Evaluation approach and methodology

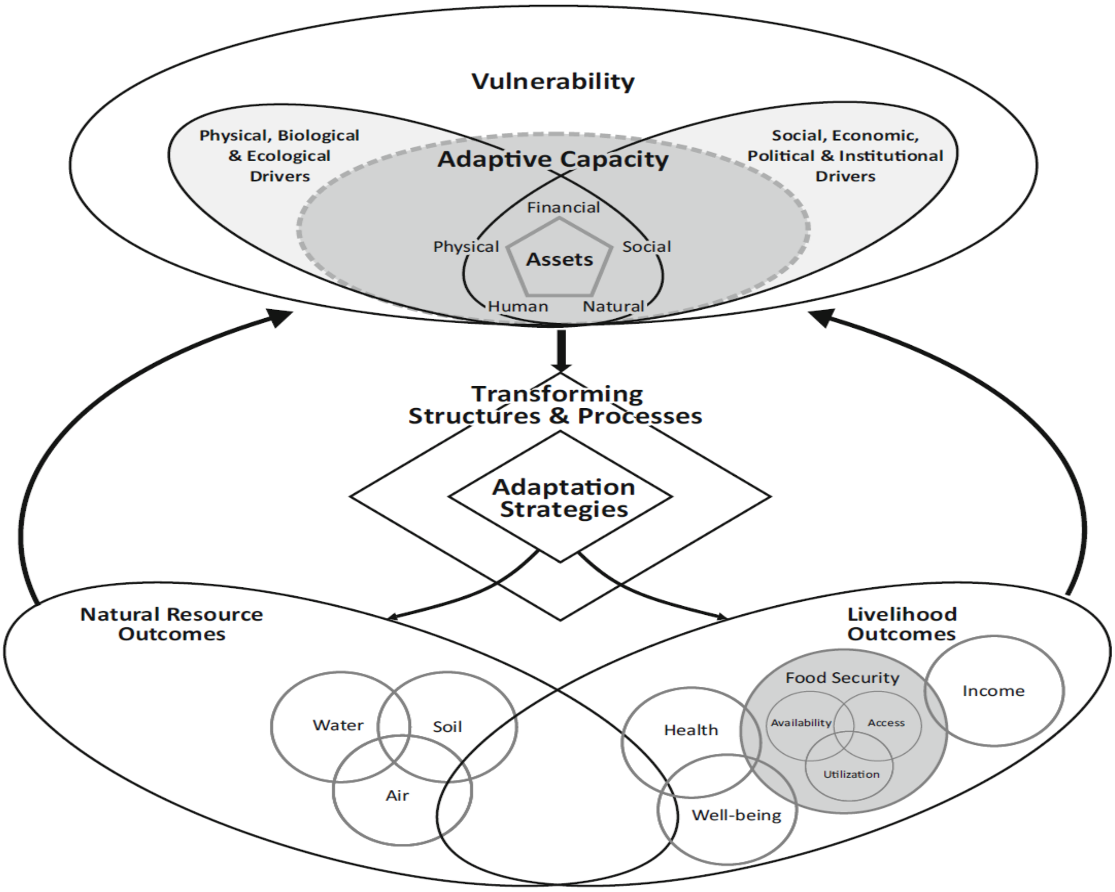
2.1 Conceptual framework

Evaluation of the intended outcomes and impacts of the CSA technologies and innovations outlined above can be pursued within the framework developed by Connolly-Boutin and Smit (2016). In this framework climate change is perceived as an external shock on biophysical and socio-economic drivers that act upon the community to shape its adaptive capacity and resilience. The two drivers also act in an interrelated manner to determine vulnerability of communities to climate extremes and shocks. However, such vulnerability effects can be aggravated if climatic changes occur in the presence of other socioeconomic drivers of vulnerability. Changing rainfall patterns in densely populated areas that are predominated by subsistence farming, for example, can make households vulnerable to long-term food insecurity if households respond to climate change by adopting detrimental or unstainable farming practices such as expanding farming to wetlands or extending cultivation to more marginal areas.

These biophysical and socio-economic drivers individually or interactively also determine the resilience (often defined in biophysical terms as the degree to which a system rebounds, recoups, or recovers from a climate change related stimulus) and capacity of communities or households to adapt to ensuing changes. Adaptive capacity is the ability of a person or a community to draw upon the asset or capital base in order to deal with the changing conditions, or in climate terms the potential or capability of a system to adapt to (to alter to better suit) climatic stimuli or their effects or impacts (IPCC 2001, Connolly-Boutin and Smit 2016). There is, therefore, a strong link between resilience, adaptive capacity and capital or access to livelihood resources or assets, themselves provided by the drivers that also influence community or household vulnerability.

The adaptive capacity is manifested in the strategies that communities employ individually or collectively to adjust to changes to maintain or improve their status—adaptation strategies. These include such actions as agricultural intensification, livelihood diversification and migration. However, for this to be realized, there needs to be some form of transforming structures and processes that allow capacity to be transformed into action/strategy. Such transforming structures include enabling environments and institutions such as government policies and development programs that could aid or constrain communities' ability to use their resources to adjust to changes. These structures emerge from the interaction of biophysical and socio-economic factors, as well as the risk and vulnerability status of the community. In Nyando, the CSVs approach is one of the transforming structures, bringing together various research and development partners to address the effects of climate variability and change. The CSVs approach provides opportunities for testing and evaluating a portfolio of CSA interventions and innovations for managing climate-related risks and adapting to climate change, and where possible mitigation benefits as well. The communities are actively engaged in the testing process to capitalize on indigenous knowledge and to promote uptake of the proven adaptation practices and technologies.

Figure 3. Climate change, food security and livelihood framework



Source: Connolly-Boutin and Smit (2016)

The CSA interventions undertaken within the CSVs can therefore be understood in the context of climate risk management and adaptive strategies aimed at helping communities cope with climate variability and adapt to climate change. These strategies and actions have impacts on natural resources and livelihood outcomes. For instance, when households within the CSVs undertake soil and water conservation measures to respond to changing rainfall patterns, this action affects soil conditions. Improvements in soil conditions will in turn enhance crop yields with potential positive implications for household food and nutrition security and income. Natural resources and livelihood outcomes that emanate from adaptive strategies are therefore synergistic as well. Adverse adaptive strategies such as extensive agriculture may involve deforestation which makes communities more vulnerable. The evaluation in this paper looks at the uptake/adoption of CSA strategies, including institutional innovations to understand their impact on livelihood outcomes—food and nutritional security, income and wealth.

2.2 Sampling and data collection

CCAFS has been collecting monitoring and evaluation (M&E) data on the participating households in Nyando. However, non-participating households were completely ignored in the M&E. Thus, the existing M&E data could not be used for impact evaluation due to a lack of counterfactual. In order to create a counterfactual, we identified villages which were very similar to the CSVs in terms of observable biophysical (i.e., temperature, precipitation, soil type, landscape position) and socio-economic (i.e., most prevalent farming system, main agricultural crops, livestock ownership and husbandry practices, market behaviours) characteristics. These villages were far enough from the CSVs to minimize "*contamination*". From these villages, we listed all the households with the help of the local administration.

Following Cochran (1963), the sample size for the study was computed as follows:

$$n = \frac{Z^2 pq}{e^2},$$

Where:

N = Sample size required
P = Estimated variance in the population, as a decimal
Q = 1-p
Z = Z-score at the desired confidence level

Because the population variability may not be easy to determine in this case, we apply the conservative figure of 50%. At 95% level of confidence, e = 0.05 and Z = 1.96. The expected basic sample size, therefore was computed as below:

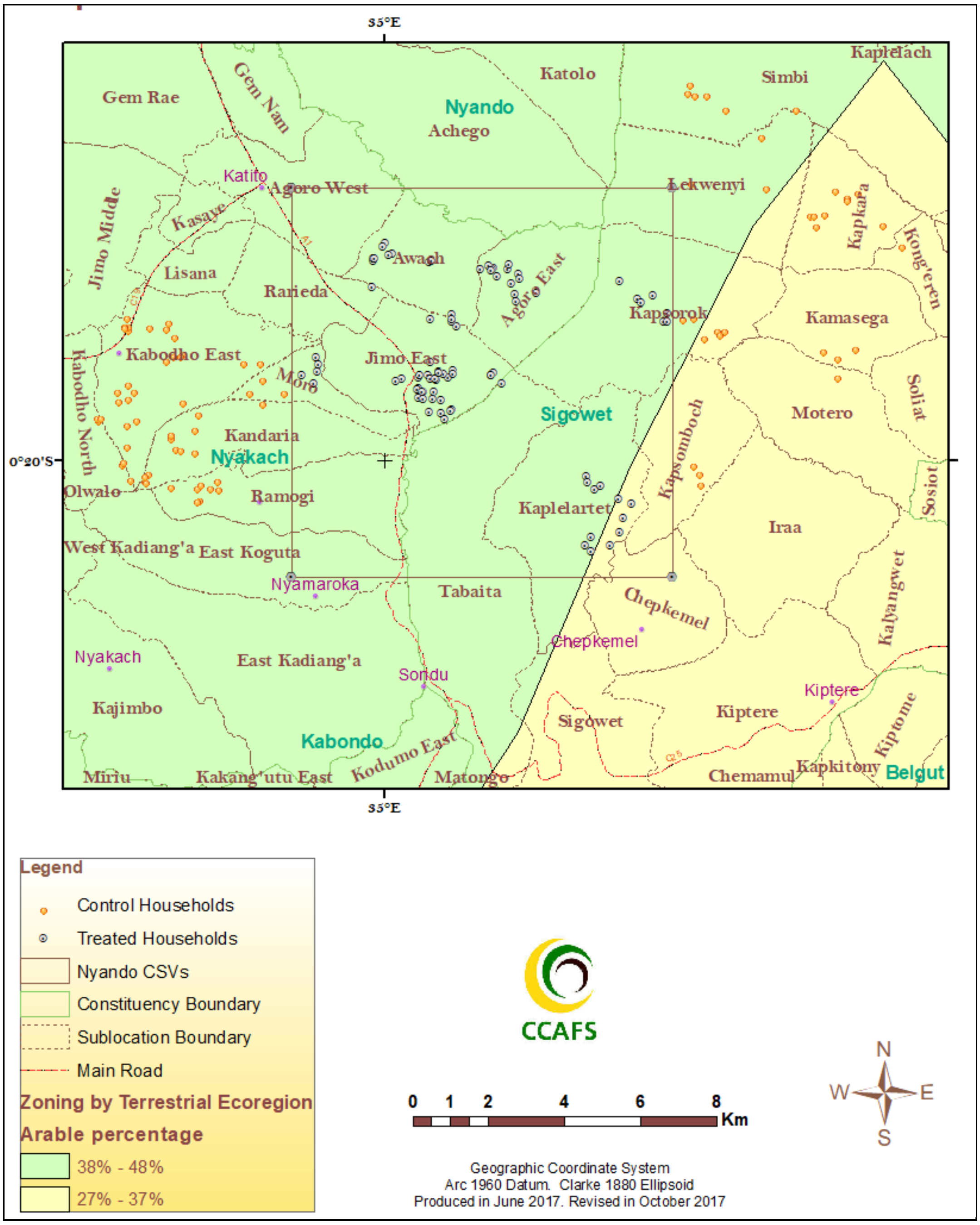
$$n = \frac{(1.96)^2(0.5)(0.5)}{0.05^2} = 385\, farm\ households$$

Assuming a non-response rate of 10%, the final sample size was estimated at 428 (i.e., 385/0.9). This sample was split in two, one-half for beneficiary households and the other half for non-beneficiary households. We, however, exceeded the sample for the participating households by two and the non-participating by three, bringing the total sample to 433.

We then used the list of participating households and the compiled list of non-participating households as the sample frames. From the list of households, we sampled those to be interviewed using an online research randomizer. Figure 4 shows the spatial distribution of the sampled households. The treated households were randomly selected from seven sublocations and included Agoro East, Jimo East, Awach, Kaplelartet, Kapkara, Lekwenyi and Kapsorok. The control households were selected from five sublocations and included Kabodho East, Olembo, Kamasega, Simbi, and Kaplelartet.

Data were collected through household survey. Household interviews were based on a structured questionnaire and captured broad issues that included household demographics, cropping patterns, livestock ownership and husbandry practices, market behaviours, adoption of CSA technologies, social capital, food consumption, credit access and livelihood options. In additional, we conducted key informant interviews (KIIs) to gain further insights into the CSA interventions and innovations that could inform the quantitative analysis applied in evaluating the impacts of the interventions. The KIIs were guided by a series of broad questions that allowed for further questions to arise as discussions progressed. The open-ended nature of these interviews helped in capturing what may not have been conceived in the conceptual framework. Information from these interviews has been used in explaining the evaluation results.

Figure 4. Spatial distribution of the treated and control households



2.3 Empirical methodology

Program evaluation often follows approaches suggested by Maddala (1983):

$$y = X\beta + \gamma I + u \tag{1}$$

Where y can be considered as one of the livelihood outcomes such as food and nutrition security, household income or wealth (asset ownership); X is a vector of farm, household and contextual characteristics that could influence livelihood outcomes and; I is a dummy indicating whether a household is practicing any one of the CSA interventions. We hypothesize that these CSA interventions could influence livelihood outcomes such as food security, household income etc. This could be because of improved availability of food brought about by planting drought- or disease- and pest-tolerant crop varieties, improved or high yielding crop varieties, soil fertility improvement measures and/or improved livestock breeds. Notably with improved yields due to improved crop varieties, households could have surplus production for sale with positive impacts on household income, possibly leading to improved purchases of diverse foodstuff (nutrition security). Holding other factors constant, therefore, the coefficient (γ) captures partial effects of household uptake of CSA technologies and interventions. However, households may self-select into uptake of interventions, and this may bias the estimates of treatment effects of CSA interventions. In other words, it is possible that some factors determining uptake of CSA intervention may also affect food security or household income. If such factors are not included explicitly in equation (1), as is the case when such variables are unobserved, then the indicator for uptake of CSA interventions in equation (1) will be correlated with the error term (u), leading to a biased estimation of γ.

One way to address this problem is to monitor households who have implemented CSA technologies and those who are not using these technologies over time, and then apply difference-in-difference (DiD) analytical techniques to isolate the impact of CSA technologies. The DiD approach calculates change in outcome indicators over time for households using CSA technologies and non-users of CSA, and then estimates the impact of CSA interventions as the difference in outcome changes for users and non-users of CSA interventions. In this study, the DiD approach could not be used as the M&E data was only available for the treatment group. We thus collected cross-sectional data covering households within the CSVs (treatment group) and those from outside the CSVs (households not participating in the project). This was important for creating a proper counterfactual group.

To address the potential selection bias, we used two approaches: Propensity Score Matching (PSM) and Endogenous Switching Regression (ESR). PSM assumes that conditioning on observable variables eliminates sample selection bias (Heckman and Navarro-Lozano 2004). Matching essentially creates an experimental condition in which uptake of CSA interventions is randomly assigned, allowing for identification of causal links between respective interventions and livelihood outcomes. Instead of directly comparing outcome and impact variables between households who have applied CSA practices and those applying conventional (non-CSA) practices, PSM restricts comparison to households that are similar in terms of observable characteristics and therefore reduces the bias that would otherwise occur if the two groups were systematically different (Dehejia and Wahba 2002).

PSM involves two stages. In the first stage, we use the entire sample of users of CSA (adopters) and non-users (non-adopters) and estimate a probit model to generate propensity scores $\boldsymbol{P}(\boldsymbol{z})$. Propensity scores are estimates of the probability that a household with a vector of characteristics $\boldsymbol{z}$, will apply CSA practices on their farms. The vector $\boldsymbol{z}$ are assumed to be those observable variables that determine whether a household applies CSA technologies. Some of these variables may be the same as variables included in X in equation (1). In this estimation, households with similar observable characteristics are likely to have similar propensity scores $\boldsymbol{P}(\boldsymbol{z})$, even if some of them may not have implemented CSA interventions. Using similarity in propensity scores, we can, therefore, construct comparable groups of households; groups of households with similar propensity scores $\boldsymbol{P}(\boldsymbol{z})$ but where one group has applied CSA practices while the other group of households has not implemented CSA interventions. In the second stage, we calculate average outcome for the two groups: those who have applied CSA interventions and the comparison group generated in stage 1. Impacts of CSA interventions (average treatment effects on the treated households - ATT) on the outcome variable (food security, household income and asset ownership) is then calculated as the difference in average outcomes between the two groups of households. The PSM estimator of the ATT is therefore the difference in outcomes between the group of households that have applied CSA interventions and the comparison group of households that have not used CSA interventions; but households in both groups have similar propensity scores. This is expressed as follows:

$$\tau_{ATT}^{PSM} = E_{P(z|I\, =\, 1)}[E\{R_1|I = 1, P(z)\} - E\{R_0|I = 0, P(z)\}] \tag{2}$$

Where $R_1$and R_0 are outcomes for households that have applied CSA practices and the comparison group of households, respectively; $I = 1$ indicates that households practice CSA and $I = 0$ refer to comparison group of households that do not practice CSA. The PSM procedure allows us to compare outcomes for comparable groups (apples with apples rather than apples with oranges) since the groups are similar in observable characteristics and hence in propensity scores.

The PSM procedure outlined above provides good estimates of the treatment effect since it allows comparison of outcomes between households implementing CSA practices and a proper comparison group with similar observable characteristics. However, PSM only addresses selection on observables. We are still left with the challenge of selection bias due to unobserved factors. Even if CSA interventions were provided at random such that households were free to decide whether to apply the CSA practices or not, such households' decisions were most likely non-random with households deciding to apply CSA practices for some reasons that we cannot observe. More informed households are investing in improved practices and applying CSA practices in an appropriate manner. Efficient and more informed households, for example, who are already food secure, could have a higher likelihood of taking up CSA interventions. In such circumstances the food security effects would be overestimated. To address this challenge, one may conduct an econometric procedure involving two-stage least squares (2SLS) instrumental variables (IVs) that controls for selection on unobservable factors (Schipmann and Qaim 2010, Wollni and Zeller 2007). The great advantage is that the PSM approach will have provided us with a reliable comparison group for such analyses. Combining PSM and econometric approaches allows us to construct a reliable comparison group and control for selection bias due to both observable and unobservable factors, thus providing reliable estimates of impact.

The challenge, however, is that basic econometric approaches assume that income or food security function would differ only by a constant term between adopters (households practicing CSA) and non-adopters (the comparison group using non-CSA practices). Yet the differences between the groups may be more systematic, such that similar factors would affect income and food security outcomes differently. For instance, adopters of CSA practices may be well informed and wealthier households who depend on non-farm income such that own-farm production may have little or no impacts on their household food security. On the other hand, non-adopters may be poorer and remotely located households whose livelihood depends entirely on agriculture and therefore own production would greatly affect household food security. Under such structural differences between adopters and non-adopters, an econometric procedure known as endogenous switching regression (ESR)—also a two-stage method involving instruments—is a more appropriate approach. A similar approach has been applied in several studies (Abdulai and Huffman 2014, Di Falco and Veronesi 2013, Di Falco et al. 2011).

Details of the ESR approach and the estimation procedure applied in this analysis are presented in Appendix 1. The approach estimates livelihood outcomes for adopters and non-adopters separately, based on the likelihood of households applying CSA interventions. Post-estimation procedures explained below then allow us to estimate impacts of CSA practices on livelihood outcomes.

2.4 Estimating the effect of CSA adoption on livelihood outcomes

We use three outcome variables—household dietary diversity score (HDDS) (food and nutrition security), domestic asset index (wealth status) and household income. HDDS is defined as the number of different foods/food groups consumed by households over a given period. It is derived by grouping all food items consumed by a household over a period of 24 hours into 12 food groups (Swindale and Bilinsky 2006). HDDS provides a qualitative measure of food consumption that reflects household access to a variety of foods. Increasing the variety of foods across and within food groups is assumed to ensure adequate intake of essential nutrients, and thus promote good health (Rashid et al. 2011). Studies from both developing and developed countries reveal strong positive association between diet diversity and nutrient adequacy (Ruel 2003). Household domestic asset index is adapted from analyses recommended for Bill and Melinda Gates funded projects. Asset index is calculated for all movable assets with each type of asset or groups of assets assigned weights which are then adjusted for age (Bill and Melinda Gates Foundation 2010). We derive this index for domestic transport and productive assets. As for household income, we apply the expenditure approach that is known to be less sensitive than the direct income measurement (Deaton 1997). The expenditure approach approximates total household income from total household expenditure on food items, non-food items and contributions expenditure.

To evaluate the income, food security and wealth (asset) effects of adoption of CSA interventions, we need to estimate the expected value of income, food security and wealth status that adopting households would have without adoption, otherwise known as conditional expectation (Maddala 1986).

The evaluation proceeds as follows. First, for a household who adopts a CSA intervention, the expected value of income/food security/wealth is:

$$E(y_{cs}|I = 1) \tag{3}$$

where y_{cs} represent livelihood outcomes (food and nutrition security – household dietary diversity; income; wealth) realized when one applies CSA interventions, and $I = 1$ implies that households chose to apply CSA technologies and practices.

For the same adopter with the same characteristics, the expected income/food security/wealth had he/she chosen not to adopt would be (Maddala 1986, pp. 257-260):

$$E(y_t|I = 1) \tag{4}$$

where y_t represents livelihood outcomes (food security – household dietary diversity; income; wealth) realized when a household does not apply the CSA interventions; again, $I = 1$ implies that households have chosen to apply CSA practices. The change in income, food and nutrition security, and wealth indicator due to adoption of CSA technologies can then be calculated following Fuglie and Bosch (1995) and Maddala (1986) as:

$$E(y_{cs}|I = 1) - E(y_t|I = 1) \quad (5)$$

In the impact assessment literature, this is the ATT. By assuming same characteristics, we hold constant all other possible causes of income, food and nutrition security, and wealth differences and therefore ensure that the difference is purely due to uptake of CSA practices[1]. The predicted difference in income represented by equation (5) is therefore due to adoption of CSA interventions.

In this study, we therefore apply the PSM procedure and augment this with an econometric approach involving ESR to estimate impacts of CSA interventions on livelihood outcomes. For an extended explanation of the estimation procedure, see Appendix 1.

3. Results and discussion

3.1 Trends in uptake of CSA technologies

Since 2011, several milestones have been achieved in Nyando CSV following the successful application of a multitude of climate-smart adaptation technologies and initiatives. We discuss some of the key resilience and adaptation-based benefits to the community based on analysis of the M&E data and key informant interviews below:

Collective action: Three strong CBOs have taken root in the seven villages, promoting collective action for agricultural development through savings, table banking and ROSCAs. While in 2011 the CBOs were made of only 17 groups with membership from 306 households, the number had risen to 55 groups with membership from 1,845 households in 2017. The savings base had also risen from USD $14,850 to USD $129,500 in the same period. Notably, 60% of women and youth now report being members of groups up from 20%. Borrowing from the groups stands at 90% and some of the main uses of the borrowed funds include purchase of food and improved farm inputs, payment of school fees and start up or expansion of micro-enterprises.

Improving access to agricultural inputs: Through the CBOs, an input supply store (agrovet) has been set up within the community, making the inputs available within a radius of 7 KM. The inputs are also availed to the farmers at more affordable rates including on credit to group members. Previously, sources of improved inputs were far from the farm households, ranging from about 17 km in lower Nyando to 44 km in upper Nyando. This constrained use of

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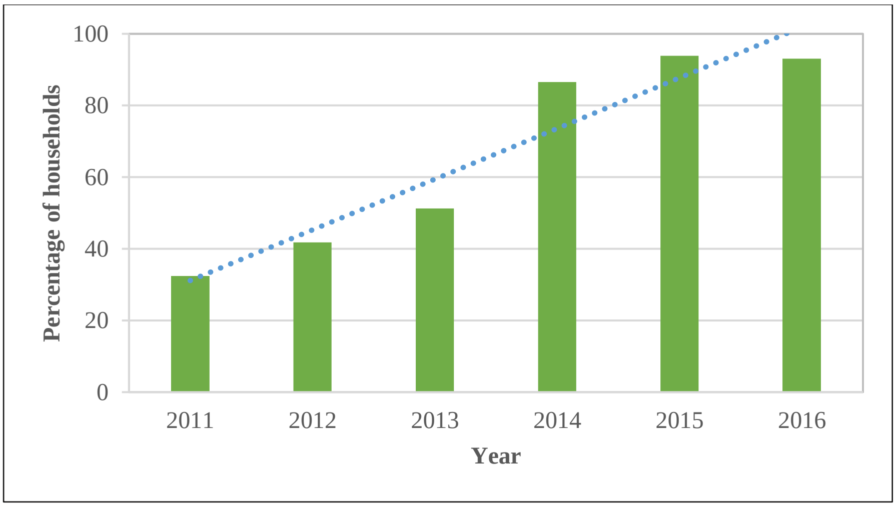
[1] Note that the unobserved factors are not ignored since λ_s remains in both equations (9) and (10) in the Appendix. The procedure simply implies that the unobserved factors have different effects depending on which regime applies. By holding λ_s constant and taking the differences in effects *($\sigma_{tv} - \sigma_{sv}$)*, we partial out effects of unobserved factors so that the estimated difference in income is purely due to market channels, devoid of any unobserved effects.

improved agricultural inputs. Extension officers from the Ministry of Agriculture, Livestock and Fisheries (MoALF), and the subsequent Kericho and Kisumu Counties after devolution, also use the community agrovet to advise the farmers, increasing uptake of improved inputs. The proportion of households using inorganic fertilizers, for example, increased from about 8% in 2011 to about 94% by 2017. From interviews with key informants, these changes are attributed to capacity building undertaken by CCAFS East Africa and partners, and increased access to improved agricultural inputs through the community-managed input supply shop.

Building resilience through multiple stress tolerant crop varieties and crop diversification: Climate change is associated with variations in temperature and rainfall, and increased pest and disease pressure. In rain-fed agriculture, drought and shortened growing seasons are major threats to food and nutritional security of agriculture-dependent households and communities. CCAFS has been working with national and international research organizations and the community to introduce drought, pest and disease tolerant, and early maturing crop varieties to smallholder farmers as part of the resilience and adaptation building effort to climate variability and change. It has also been promoting diversification of crops. All these measures aim to minimize yield losses even with the changing climate. Among the new and/or improved crop varieties in Nyando are pigeon peas, and sorghum varieties such as *KARI Mtama 2*, *KARI Mtama 4*, *Seredo*, and *Serena* which are fast maturing and tolerant to water logging. There are also improved cassava varieties which are resistant to the mosaic virus, improved potato varieties which are fast maturing and tolerant to drought, and tissue culture bananas which are resistant to bacterial wilt.

Results show that households are increasingly adopting improved, climate resilient crop varieties (Figure 5).

Figure 5. Uptake of improved crop varieties in Nyando



The number of farmers introducing improved crop varieties has gradually been on the rise from 2011 (baseline). The KII results confirmed that although drought-tolerant and other improved varieties were becoming widespread in Nyando as a climate risk management and adaptation strategy, adoption levels were much higher in the CSVs. This was attributed to collective action in such villages, presence of demonstration farms and improved access to seeds. There has been a significant increase in the number of households adopting at least three more new crops between 2011 and 2012, and between 2013 and 2014 (Recha et al.

2017). These crops include cowpeas, pigeon peas, groundnuts, green grams, cassava, sweet potatoes, sorghum, finger millet, bananas, butternuts, watermelons, kales, cabbages, collards, onions, tomatoes, and indigenous vegetables.

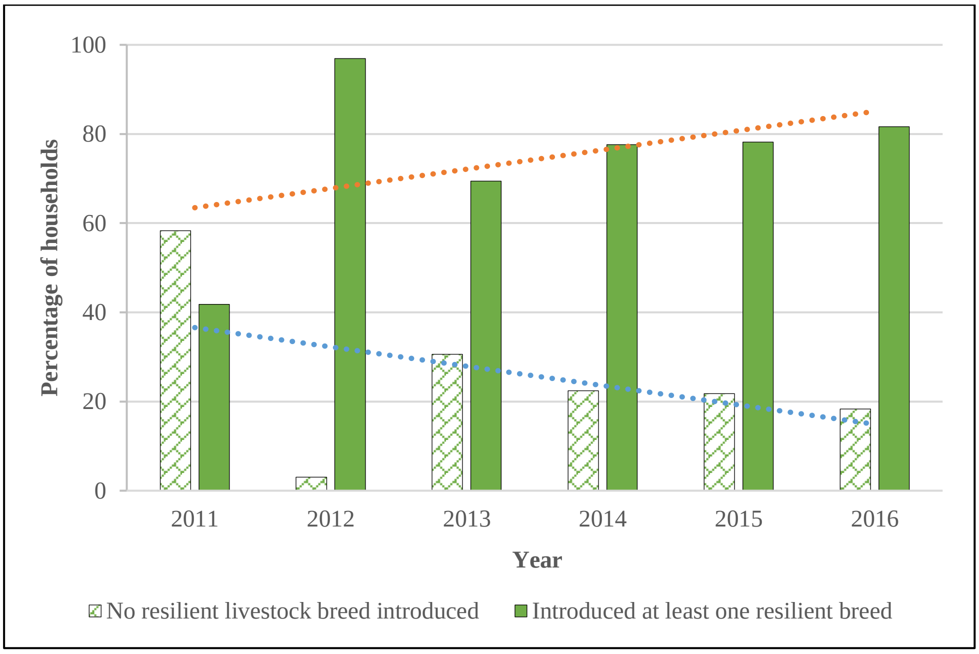
Improved agronomic management - early planting, crop rotation and intercropping: Early planting—planting field crops before or immediately after the onset of the rains—ensures optimal use of the short rain season and efficient utilization of accumulated nutrients (nitrogen flush) from organic sources during the dry season. Early planting in Nyando has been enhanced by improving dissemination and access of weather information. In addition, farmers are increasingly intercropping various crops that include maize, beans, cowpeas, green grams, sorghum, indigenous vegetables and sweet potatoes (Recha et al. 2017). Some farmers practice mixed intercropping where the different crops are planted at the same time, while others practice relay intercropping where the different crops are planted at different times. Intercropping is helping farmers spread the risk of crop failure as the different crops have different patterns of growth and are affected by different pests and diseases, therefore contributing to building the resilience of Nyando farmers in dealing with climate-related risks. Crop rotation involving legumes has equally been embraced by the farmers because the nitrogen-fixing bacteria in the roots of legume plants minimizes the amount of fertilizers applied. This reduces input costs and has mitigation co-benefits of reducing carbon dioxide emissions attributed to fertilizers.

Intercropping involves growing two or more different crops together on the same piece of land with the aim of increasing production per unit area of land. Intercropping has multiple benefits including minimizing soil erosion and reducing depletion of soil nutrients, reducing the risk of total crop failure, providing diverse products on the same parcel of land, suppressing weeds and improving water use efficiency. Recha et al. (2017) found that intercropping is increasingly used by farmers in Nyando. The various crops intercropped include maize, beans, cowpeas, green grams, sorghum, indigenous vegetables such as Crotolaria species, and sweet potatoes. Some of these intercrops are planted at the same time (mixed intercropping), while others are planted at different times (relay intercropping). Cereal-legume intercrops such as maize/sorghum with cowpeas, beans and pigeon peas have been highly recommended by Nyando partners because they provide symbiotic benefits.

Improving incomes and climate resilience through improved small ruminants: Adaptation through farm-level breed management can be achieved through improving the genetic potential of livestock breeds to produce fast growing, bigger and hardy animals. Cross-breeding of exotic and indigenous animals combines the high yield and early maturity traits of exotic breeds with the hardiness, disease resistance and adaptability traits of local breeds. Between 2012 and mid-2013, almost all the households in Nyando CSV kept poultry, while about 60% of these households also kept cattle, specifically the indigenous Zebu breed. Likewise, about 48% of the households kept indigenous sheep and goats, specifically the Small East African sheep, and the Small East African indigenous goats. The indigenous sheep and goat breeds have low productivity, and often showed poor recovery from drought and diseases, and there was a clear need to improve these indigenous breeds through cross-breeding. Thus, in partnership with the Nyando CSV, CBOs and ILRI, we introduced resilient breeds of Galla goats and Red Maasai sheep as improved/exotic breeds.

The Galla goat is preferred because it is well adapted to the dry conditions, grows faster and matures about six months earlier than the indigenous goats, and produces more milk (Ojango et al. 2016). Female Galla goats have a longer productive life, as they are able to breed and rear kids for up to 10 years. In addition, the Galla goat is docile and easy to handle. Similarly, Red Maasai sheep grow faster, are resistant to internal parasites, tolerant to trypanosomes, drought and heat stress, and suitable for meat production. The cross-breeds of the Galla goats and the local goats, and of Red Maasai sheep and the local sheep would still grow faster than the local breeds. Moreover, the cross breeds attract higher prices in the local markets, almost three times the prices of the local breeds because of higher weight, better body condition and tender meat. The small ruminants are also less labour intensive compared to the large ruminant cattle because they feed less and drink less water. Moreover, their short reproductive cycle compensates for the meat and milk production that would be expected from the cattle. Figure 6 shows the trends in uptake of improved livestock breeds.

Figure 6. Uptake of improved livestock breeds in Nyando



According to Figure 6, about 60% of households in the Nyando CSVs had not introduced any form of improved or resilient livestock breeds as of 2011. This changed from 2012 when 70 breeding Galla goats were introduced, and mid-2013 when 30 breeding Red Maasai sheep were introduced. Uptake has since been on an upward trend. From the 100 breeding units, about 3,540 cross-breeds (a third of the sheep and goat population in the experimental villages) were recorded in 2017. It is projected that the Galla goat and Red Maasai sheep crosses will replace the indigenous breeds fully in all the CSVs over a period of five years. Households with indigenous breeds of goats, sheep and poultry earn extra income during the main growing season which averages between $300 and $350, which will undoubtedly improve the resilience of smallholder farmers. Improved breeds have an increased market price of $80-200 due to higher live weight and more tender meat, which is three times higher than the local Small East African goat and sheep breeds.

Agroforestry for farm diversification and resilience: Agroforestry integrates trees into crop and livestock production and across agricultural landscapes. Trees diversify land use and farming systems, providing additional livelihood and environmental benefits. Agroforestry contributes to building ecological resilience by providing carbon sinks thereby removing GHG from the atmosphere. The high uptake of intercropping in Nyando, including intercropping of trees and annual crops (Recha et al. 2017), provides the benefits of minimizing the risk of soil erosion by wind and surface runoff, removing nutrients from deeper soil layers to surface layers, and providing soil organic matter through decomposition of leaf biomass and roots. Farmers can accrue additional benefits by using leguminous tree species that will fix nitrogen in the soil and provide fodder to farm animals. CCAFS is collaborating with a development partner, Vi-Agroforestry to promote agroforestry in Nyando, focusing on trees which grow faster under water stress and have multiple uses. About 45 tree nurseries with a capacity of 500,000 tree seedlings per season have been supported, some of which are owned by self-help groups. More than half of the tree nurseries are owned by women. By 2017, over 150,000 high quality seedlings had been produced and about 80,000 multipurpose trees planted. Dry seasons have provided challenges to young trees. Similarly, free-range grazing of ruminants has been a challenge for the accelerated uptake of agroforestry in Nyando as they feed on or destroy the young trees.

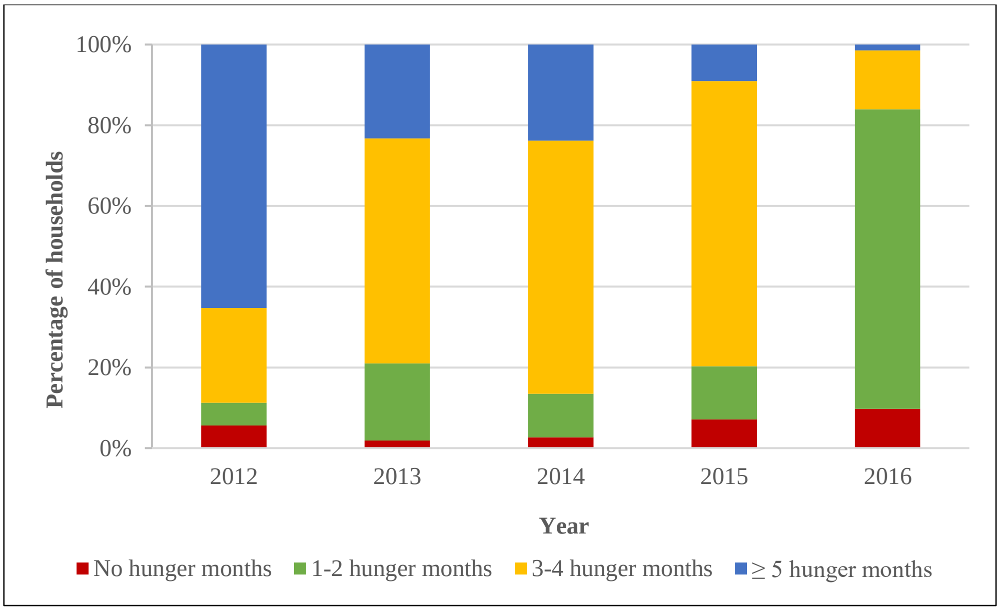
Soil and water management: The soil and water conservation measures in Nyando CSV include water-harvesting pans, ploughing across contours, use of terraces and stone bunds (Recha et al. 2017), with terraces mainly preferred by the farmers. Terraces were introduced to reduce the velocity of water runoff by breaking the length of the slope that run-off. There has been a gradual increase in the proportion of households building terraces from 0.1% in 2011 (baseline) to 35% in 2017. The Kericho and Kisumu County Departments of Agriculture Livestock and Fisheries are working in collaboration with CCAFS and the farmers in the Nyando CSVs to promote water harvesting, terracing, and contour farming. As a result, 164 new water storage pans have been established across the CSVs, enabling farmers to irrigate their homestead gardens and agroforestry systems during the dry periods. Most farmers use watering cans, while others use manual and solar water-pumps along with open channels and pipes for the irrigation. A total of 35 water pans have been supported with liners to minimize water loss through seepage. A total of 30 km of terraces and 15 km of contoured grass strips have been constructed as well.

A water pan in Nyando. Photo: J. Recha (CCAFS)

Improved beekeeping for income diversification: In Nyando, farmers are diversifying into beekeeping for income, contributing to resilience of the environment and reducing GHG emissions. Beekeeping is a classic example of synergy between resilience and adaptation building initiatives and mitigation co-benefits. Apiculture in Nyando CSVs incorporates adaptation through pollinating crops and generating income, as well as mitigation through enhancing conservation of natural vegetation and biodiversity for nectar sources. Previously, farmers relied on traditional beekeeping with a yield capacity of 5 kg of honey per beehive annually. In 2009, Kenya's MoALF and World Neighbours partnered with self-help groups and CCAFS in Nyando to introduce improved beehives, coupled with training on management. By 2017, 18 beekeeping groups had been established across the CSVs with a total of 225 beehives. Of the 18 groups, six are women's groups while the rest have mixed membership with 70% of their members being women and youth. Honey yields are estimated at 10 kg per beehive per harvest with a possibility of up to six harvests per year, translating to 60 kg annually per beehive.

Improving food and nutrition security: While food security remains a major challenge in the Nyando CSVs, progress has been observed in the last few years as shown in Figure 7. In 2011, very few households were food secure, reporting no hunger months throughout the year. By 2016, about 10% of the households reported being food secure throughout the year. The proportion of households reporting 1-2 months of hunger dropped from 81% in 2011 t to 74% in 2016. The trends in Figure 7 indicate that the proportion of households experiencing more than 5 months of hunger in a year has been declining from 2012.

Figure 7. Household food security



It is also evident from Figure 7 that the proportion of households experiencing no hunger at all throughout the year has gradually increased between 2011 and 2016. This was consistent with information from the KIIs. A significant number of key informants indicated that before the interventions, most households would experience as high as 8 months of hunger in a year (please see the direct quote below). This has since dropped to 2-3 month a year, on average. In a good year, however, most households would be food secure throughout the year.

> "*Before 2012, my family could suffer up to 8 months of hunger. This has since changed as I have now expanded and diversified my farming. In a good year, I can harvest crops to keep my family food secure for even up to 2 years. Indeed, I sell part of my harvest to meet weeding expenses"—said one farmer in Agoro East.*

Improving food security has been attributed to uptake of improved crop varieties which are high yielding and drought-tolerant. Other likely contributing factors include climate-smart adaptation technologies and practices such as increased use of fertilizers, mixed cropping, early planting, planting of early maturing varieties and, in some cases, using small scale irrigation.

3.2 Adoption and impact of CSA technologies and practices

In this section, we present and discuss the results of the analyses undertaken to evaluate the impacts of CSA technologies and practices on household welfare indicators (livelihood outcomes). We begin by providing a summary description of key variables used in the analyses before discussing the adoption of specific CSA technologies and practices. We then present findings on the impacts of CSA technologies on household indicators of food and nutrition security, household income, and wealth (assets) status.

Summary statistics of variables used in analysis

We explore and describe differences between adopters and non-adopters of CSA technologies and practices. We first look at these differences in terms of key livelihood outcome variables of dietary quality, household income and asset ownership (as described in section 2.4), before exploring additional variables used in our econometric analysis. We restrict our descriptive analyses here to the three CSA technologies and practices that we analyse in this study: improved and multiple stress-tolerant crop varieties, improved and better adapted small ruminants, and integrated soil and water conservation measures. As expected, CSVs account for the largest proportion of households adopting the three CSA practices (Table 1), thus underscoring the role of CSVs approach in promoting CSA technologies and practices, and innovations. Households adopting CSA technologies and practices also exhibit significantly superior diet diversity. This is especially so for households adopting drought-tolerant crop varieties and improved small ruminants. Indeed, further analyses show that households adopting improved small ruminants consume significantly more of own-produced animal source food (ASF) such as eggs and milk, as well as own-produced drought-tolerant crops. It is therefore not surprising that adopters of improved small ruminants have a slightly superior diet diversity score. Our descriptive analyses also reveal that households adopting improved multiple stress-tolerant crop varieties and improved small ruminants are significantly wealthier than non-adopters. Adopters of improved multiple stress-tolerant crops have even significantly higher household income. We also note that adopters of improved small ruminants tend to sell significantly more of own-produced ASF (eggs and milk), live animals (goats) and chicken. This is an indication of possible impacts of these technologies on household welfare that we analyse in detail in the next section.

In terms of possible determinants of these outcomes, we find that adopters and non-adopters of improved multiple stress-tolerant crop varieties differ significantly in farming experience, age of household head, collective action and access to weather forecast information. Instinctively, social capital (group membership) was significantly more predominant among adopters even at the time of project inception. While this difference has grown over time (from 31% in 2011 to 84% in 2016), it is likely that group membership played a key role in targeting possible project beneficiaries. The same patterns play out for adopters of improved small ruminants, but here land comes out significant with adopters having significantly large holdings. This is possibly due to the need for grazing area for livestock.

Our summary statistics show that 76% of sampled households use improved seed varieties with maize exhibiting the largest proportion of adopters (Figure 8 and Figure 9). This is probably informed by the dominance of maize in diets among other staples. Food expenditure patterns also reveal the predominance of maize in household staple diets (Figure 10). As can be seen from Table 1, adoption of improved and multiple stress-tolerant crop varieties is higher in the CSVs, accounting for 66% of those who have adopted improved and multiple stress-tolerant crop varieties. Similarly, CSVs account for the largest proportion of households adopting improved and better adapted small ruminants (80%), and integrated soil and water conservation measures (65%).

Figure 8. Uptake of improved seeds

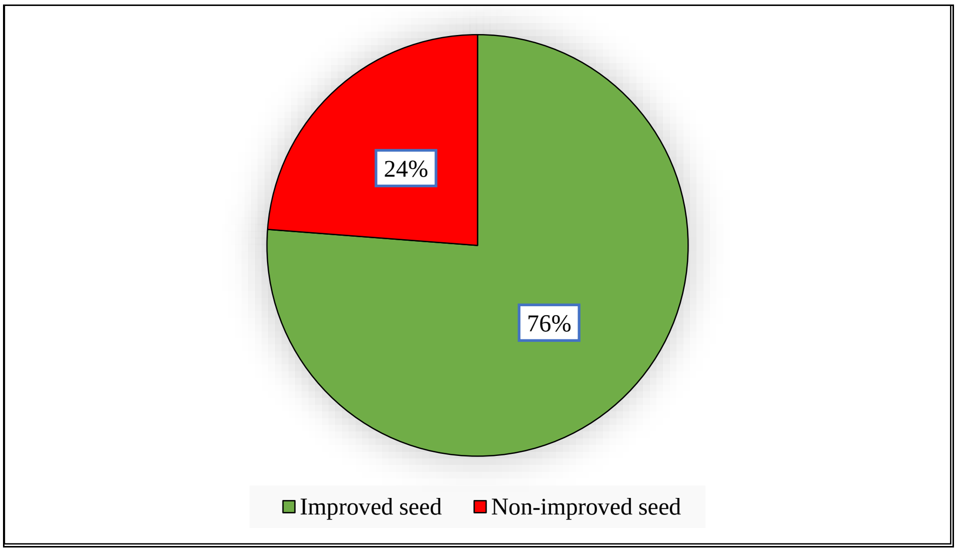


Figure 9. Uptake of improved seeds by crop

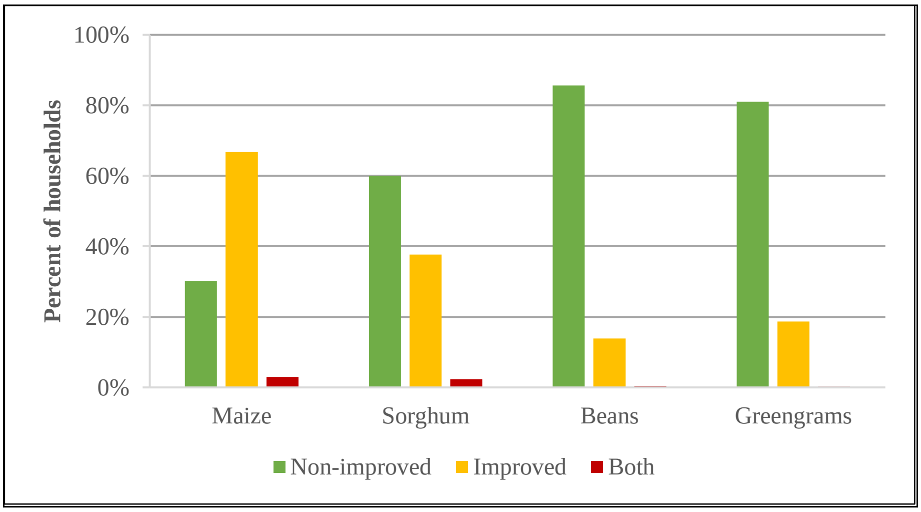


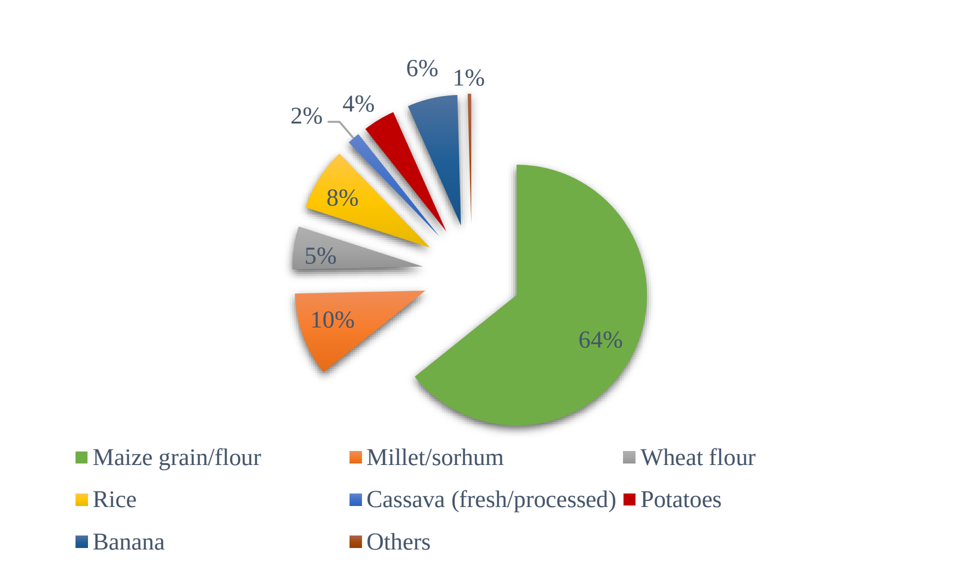
Table 1. General differences between adopters and non-adopters of CSA technologies and practices

	Improved multiple stress-tolerant crops				Improved and better adapted small ruminants				Integrated soil and water conservation			
	Adopters		Non-adopters		Adopters		Non-adopters		Adopters		Non-adopters	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Residents in CSVs *(%)*	66.3***	3.3	34.7	3.2	79.8***	4.2	41.6	2.7	64.9***	3.4	38.0	3.1
Household dietary diversity *(count)*	7.31***	0.14	6.80	0.13	7.52***	0.18	6.92	0.11	7.02	0.14	7.074	0.130
Domestic asset index	39.28***	3.37	26.04	3.33	39.50*	4.83	30.43	2.73	37.65**	3.53	28.263	3.217
Household income/adult equivalent (000)	94.05***	16.45	45.84	60.68	63.85	10.80	70.54	10.54	70.88	13.86	67.52	10.79
Gender of operator *(male dummy) (%)*	75.0	3.0	73.3	3.0	84.0***	3.8	71.4	2.5	75.4	3.1	73.1	2.9
Total land owned *(acres)*	3.17	0.20	3.05	0.21	3.54*	0.33	2.98	0.16	3.28	0.23	2.96	0.19
Educational status of household head												
No formal education	10.1	2.1	10.2	2.0	8.5	2.9	10.6	1.7	9.9	2.2	10.3	2.0
Primary education	56.7	3.4	61.8	3.2	57.4	5.1	60.0	2.7	57.6	3.6	60.7	3.1
Secondary education	25.0	3.0	22.2	2.8	22.3	4.3	23.9	2.3	22.5	3.0	24.4	2.8
Tertiary/post-secondary education	8.2	1.9	5.8	1.6	11.7**	3.3	5.6	1.3	9.9**	2.2	4.5	1.3
General farming experience *(years)*	22.7*	0.97	20.8	1.01	22.7	1.5	21.4	0.8	21.0	1.08	22.2	0.93
Age of operator *(years)*	52*	1	50	1	52	1	50	1	50	1	51	1
Household size *(number of people)*	6.07**	0.16	5.58	0.16	6.38***	0.25	5.66	0.12	5.98*	0.18	5.69	0.14
Household adult equivalent	3.07***	0.07	2.85	0.07	3.23***	0.11	2.89	0.05	3.02	0.07	2.91	0.06
Proportion of household that received forecast on:												
Onset of rains *(%)*	87.0*	2.3	81.8	2.6	85.1	3.7	84.1	2.0	90.0***	0.02	79.8	0.03
Extreme weather occurrence *(%)*	88.0***	2.3	77.8	2.8	88.3*	3.3	81.1	2.1	86.9**	0.02	79.3	0.03
Member of group currently *(%)*	83.7***	2.6	62.2	3.2	85.1***	3.7	69.0	2.5	78.5***	0.03	67.8	0.03
Member of group in 2012 *(%)*	30.8***	3.2	14.7	2.4	28.7**	4.5	20.6	2.2	24.1	0.03	21.1	0.03
Consumption of own-produced animal source food (ASF) in 2016												
Quantity of eggs produced	439**	147	170	52	775***	318	167	38	402	155	219	59
Quantity of eggs consumed	271**	107	72	12	413***	225	100	21	263*	116	93	15
Quantity of eggs sold	206	106	79	47	467**	250	49	18	200	114	93	46
Quantity of milk produced	591	61	501	59	1,065***	140	400	34	556	56	534	62
Quantity of milk consumed	365	33	378	87	738***	202	270	21	470**	102	294	28

	Improved multiple stress-tolerant crops				Improved and better adapted small ruminants				Integrated soil and water conservation			
	Adopters		Non-adopters		Adopters		Non-adopters		Adopters		Non-adopters	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Quantity of milk sold	224	40	229	63	583***	155	128	20	236	68	219	41
Sale of small ruminants and chicken in 2016												
Number of goats sold	1.3**	0.2	0.9	0.2	2.1***	0.3	0.9	0.1	1.3**	0.2	1.0	0.1
Number of sheep sold	0.9	0.2	0.7	0.2	1.0	0.2	0.7	0.1	1.0*	0.2	0.6	0.1
Number of chicken sold	5.1	1.0	4.8	0.7	11.1***	2.4	3.4	0.3	6.2**	1.0	4.2	0.7
Quantities of main crops produced, consumed and sold												
Maize harvested	2.9*	0.3	4.3	0.9	5.0*	0.9	3.2	0.6	4.0	1.0	3.3	0.4
Maize consumed	2.5	0.2	3.0	0.8	3.2	0.4	2.7	0.6	3.3	1.0	2.4	0.2
Maize sold	0.6*	0.1	1.1	0.3	1.9***	0.7	0.5	0.1	0.9	0.3	0.8	0.3
Sorghum harvested	2.1	0.4	1.5	0.6	2.7*	0.8	1.5	0.4	2.6**	0.8	1.1	0.1
Sorghum consumed	1.8	0.4	1.3	0.6	2.3	0.8	1.3	0.4	2.3**	0.8	1.0	0.1
Sorghum sold	0.4*	0.2	0.2	0.1	0.4	0.1	0.2	0.1	0.4	0.2	0.2	0.1
Beans harvested	0.5	0.2	0.2	0.1	0.7**	0.4	0.2	0.1	0.4	0.2	0.3	0.1
Beans consumed	0.4*	0.2	0.1	0.0	0.6**	0.4	0.2	0.1	0.4	0.2	0.2	0.0
Beans sold	0.2	0.2	0.1	0.0	0.2	.01	0.1	0.1	0.2	0.2	0.1	0.0
Green-grams harvested	0.3*	0.1	0.1	0.0	0.2	0.1	0.2	0.1	0.3	0.2	0.1	0.0
Green-grams consumed	0.3	0.2	0.1	0.0	0.3	0.2	0.1	0.1	0.3*	0.2	0.1	0.0
Green-grams sold	0.1*	0.1	0.0	0.0	0.2**	0.2	0.0	0.0	0.1*	0.1	0.0	0.0
Number of observations	*208*		*225*		*94*		*339*		*191*		*242*	

, **, * Mean values are significantly different at 10%, 5%, and 1% level, respectively.*

Figure 10. Expenditure on staples



Propensity score matching and regression results

The descriptive analyses in the previous sections revealed significant differences in livelihood and resilience of the community to shocks and climate extremes between adopters and non-adopters of CSA technologies and practices. These differences are also evident for welfare indicators—household income, asset ownership and food and nutrition security measures (i.e., HDDS). Similarly, differences were shown for various other determinants of these livelihood outcome indicators. To analyse causality and develop more meaningful statements about impacts, we thus, applied the two approaches outlined in section 2: propensity score matching and endogenous switching regression.

We begin this effort by presenting the results of the PSM that would provide reliable estimates of impacts when there is limited selection bias due to unobserved factors. The PSM process begins with the estimation of propensity scores, $P(\boldsymbol{z})$. In the specification of the probit model, we avoid the use of potentially endogenous variables, as this could cause problems in interpretation of results (Caliendo and Kopeinig 2008). The estimated propensity scores are used to derive ATT of CSA interventions (improved and multiple stress-tolerant crop varieties, improved and better adapted small ruminants, and integrated soil and water conservation measures) on the three livelihood outcomes (HDDS, asset index and household income). We use nearest neighbour matching (NNM) and kernel-based matching (KBM) methods and impose the common support condition to ensure proper matching. The matching procedure was conducted with STATA 14 software, following steps described by Leuven and Sianesi (2003).

Table 2 shows ATT for the three CSA technologies and practices. Adoption of CSA technologies and practices has a significant impact on livelihood indicators of food and nutrition security, household income and wealth. Adoption of improved and multiple stress-tolerant crop varieties increases household dietary diversity by between 8–11 percentage points [2], while it increases asset index by 53–60 percentage points and more than doubles household income per adult equivalent. Similarly,

[2] HDDS increases from 6.8 to 7.3 (kernel matching) and from 6.6 to 7.3 (NN matching) representing an 8–11 percentage point increase. Similarly, asset index increases from 25.7 to 39.4 (kernel matching) and from 24.7 to 39.4 (NN matching) representing a 53–60 percentage point increase.

adoption of improved and better adapted small ruminants increases HDDS by 6–10 percentage points[3], and also increases asset index by 22–51 percentage points. Income effects of improved and better adapted small ruminants are not significant. We therefore conclude that adoption of CSA technologies and practices has a positive and significant impact on food security and asset index and income to some extent, with higher impacts on asset index. The impact of integrated soil and water conservation practices is marginal and largely insignificant.

Table 2. Average treatment effects of CSA technologies and practices, and results of sensitivity analyses

Matching algorithm	Welfare outcome	Average treatment effect (ATT)	T-statistic	Critical level of hidden bias (Γ)	Treated (n)	Control (n)
Treatment effect of improved and multiple stress-tolerant crop varieties						
Nearest neighbour	HDDS	0.71	2.17**	1.40-1.45	203	205
	Domestic asset index	14.69	2.78***	1.80-1.85	206	224
	Household income/AE *(000)*	51	2.62***	1.45-1.50	204	210
Kernel	HDDS	0.52	2.23**	1.30-1.35	203	205
	Domestic asset index	13.62	2.81***	1.80-1.85	206	224
	Household income/AE *(000)*	106	1.81**	-	204	210
Treatment effect of improved and better adapted small ruminants						
Nearest neighbour	HDDS	0.717	2.14**	1.30-1.35	92	339
	Domestic asset index	13.47	1.98**	1.00-1.05	91	294
	Household income/AE *(000)*	16.32	1.21	-	94	330
Kernel	HDDS	0.44	1.81*	1.30-1.35	92	339
	Domestic asset index	7.23	1.21	-	91	294
	Household income/AE *(000)*	-9.64	-0.54	-	94	330
Treatment effect of integrated soil and water conservation measures						
Nearest neighbour	HDDS	-0.271	-1.23	1.15-1.20	188	242
	Domestic asset index	8.43	1.76	-	184	238
	Household income/AE *(000)*	13.02	0.53	-	182	238
Kernel	HDDS	-0.27	-1.72	1.15-1.20	188	242
	Domestic asset index	6.20	1.16	-	184	238
	Household income/AE *(000)*	-6.93	-0.38	-	182	238

*Note: *, **, and *** mean values are significantly different at the 10%, 5%, and 1% levels, respectively. The z-values for the ATTs are based on bootstrapped standard errors with 500 replications.*

Despite the general ability of PSM to control for selection bias, the estimates are only valid subject to two conditions: i) balancing in covariates is achieved, and ii) there is no systematic farmer heterogeneity due to unobservable effects (Caliendo and Kopeinig 2008, Dehejia and Wahba 2002). The objective of estimating the propensity scores is to balance the distribution of variables relevant to

[3] HDDS increases from 7.1 to 7.5 (kernel matching) and from 6.8 to 7.6 (NN matching) representing a 6–10 percentage point increase. Similarly, asset index increases from 32.7 to 39.9 (kernel matching) and from 26.4 to 39.9 (NN matching) representing a 22–51 percentage point increase.

the matching process. Balancing tests are, therefore, necessary after matching to determine if the matching process has reduced the bias by eliminating differences in covariates. The results reveal substantial reduction in bias due to balancing achieved via statistical matching (see Table 2a in Appendix 2), underlining the fact that systematic differences that are due to observable factors are properly eliminated.

To test for potential hidden bias due to unobservable factors, we use Rosenbaum bounds test (Rosenbaum 2002). Assuming two individuals have the same observed covariates $\boldsymbol{z}$ (as implied by the matching procedure), the two matched observations would differ in their odds of uptake of CSA technologies and practices only by the difference in unobserved covariates, which is measured by the parameter $\boldsymbol{\Gamma}$. The test procedure involves changing the level of $\boldsymbol{\Gamma}$ and deriving the bounds on the significance levels of the ATT under the assumption of endogenous self-selection into adoption. This allows for identification of the critical levels of Γ at which the estimated ATT would become insignificant.

Results of this test are shown in Table 2. Using the example of impacts of drought-tolerant crops on HDDS, the critical values for hidden bias ($\boldsymbol{\Gamma}$) are 1.40-1.45 with NNM and 1.30-1.35 with KBM. The lowest value of Γ=1.3 implies that individuals that have the same $\boldsymbol{z}$-vector would have to differ in their odds of adopting drought-tolerant crops by a factor of 1.3 (30%) to render the ATT for HDDS insignificant. As can be seen from Table 2, some of the critical values for hidden bias are quite low, indicating potential for hidden bias that would invalidate our findings.

In the presence of such hidden bias (selection into adoption due to unobserved factors), matching techniques do not provide efficient estimates of impact. We, therefore, augment the matching approach with econometric procedure involving ESR. By applying this procedure on a sample of matched adopters and non-adopters we ensure that our results are robust to self-selection due to both observable and unobservable characteristics. Given the PSM results that revealed insignificant impacts of improved and better adapted small ruminants on income as well as integrated soil and water conservation interventions (Table 2), we restrict the ESR analyses to adoption of improved and multiple stress-tolerant crop varieties, as well as improved and better adapted small ruminants. The analytical approach for ESR is already outlined in section 2 and here we present the estimation results.

Adoption and impacts of improved and multiple stress-tolerant crops on household dietary diversity score, asset index and income

Results of the ESR estimates for impact of improved and multiple stress-tolerant crops on food security are presented in Table 3. Consistent with our descriptive analyses, we find that residence in CSVs significantly increases chances that households will adopt improved multiple stress-tolerant crops. This confirms the role of CSVs approach in promoting uptake of these improved multiple stress-tolerant crop varieties. Group membership (social capital) plays a key role in targeting households since it positively and significantly influences the likelihood of uptake. This is possibly because the groups may have formed the avenues for mobilizing communities within the CSVs. Other factors playing significant roles in the uptake of drought-tolerant crop varieties include ethnicity, with the Luo ethnic group having a higher likelihood of adopting improved multiple stress-tolerant crops. As expected, we also find that households that receive forecast on varied weather conditions also have a higher likelihood of adopting improved multiple stress-tolerant crops.

Turning to the estimations in the last two columns of Table 3 (adopters and non-adopters of improved multiple stress-tolerant crops), we notice the difference in the determinants of HDDS between adopters and non-adopters. This justifies the use of ESR which assumes structural differences between adopters and non-adopters of improved multiple stress-tolerant crops. Low education levels significantly reduce HDDS among adopters while education plays no role among non-adopters. Secondly, while non-farm income has significant influence on HDDS among both categories, income from micro-enterprises and formal employment only influences HDDS among adopters. Ethnicity also only matters for non-adopters. As discussed in the analytical framework, we also interpret the covariance terms reported in the lower segment of Table 3. The covariance term for adopters is significant and negative, indicating presence of positive selection bias. Therefore, households with above average dietary diversity have a higher probability of adopting improved multiple stress-tolerant crops.

We undertake similar analyses for impacts of improved multiple stress-tolerant crops on asset index and the results of the estimation are presented in Table 4. Again, we find evidence of positive selection bias, whereby households with above average asset index self-select into adoption of improved multiple stress-tolerant crops. Indeed, the adoption equation in the first two columns shows that those with higher asset index at the beginning of the project[4] had higher chances of adopting the improved multiple stress-tolerant crops. Similarly, households who were members of groups at project inception (2012) also had higher chances of adopting drought-tolerant crops, underscoring the role of social networks in mobilizing households for CSA interventions. On the other hand, households who earn more income from formal employment are less likely to adopt drought-tolerant crops, possibly opting to buy food rather than producing their own staples. Similar to the HDDS (Table 3), the analyses reveal structural differences as exemplified by results in the last two columns for adopters and non-adopters of improved multiple stress-tolerant crops.

[4]Asset index is derived based on the age of respective asset elements. Lagged asset index refers to assets that are 7 years or more. The choice of 7 years is informed by the assumption that the CSV project begun in 2012, which is less than 7 years back. We do this to avoid reverse causality that would result if we used overall asset index – asset index informing the decision to adopt drought-tolerant crops.

Table 3. Adoption of improved multiple stress-tolerant crops and determinants of household dietary diversity

Independent variables	Improved multiple stress-tolerant crops adoption (1/0)		Determinants of household dietary diversity			
			Adopters of improved multiple stress-tolerant crops		Non-adopters of improved multiple stress-tolerant crops	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	-0.014	0.009	0.004	0.012	-0.019***	0.007
Primary education	-0.170	0.142	-0.499*	0.284	-0.751	0.507
Secondary education	-0.260	0.190	-0.399	0.362	-0.366	0.356
Tertiary/college/university	-0.031	0.402	0.431	0.790	-0.546	0.597
Occupation of household head						
Farm wage employment	-0.901***	0.182	3.225***	0.727	1.275	0.914
Non-farm employment	-0.031	0.185	0.025	0.267	-0.279*	0.149
Micro-enterprise	-0.044	0.137	0.719	0.443	0.411	0.403
Other employment	-0.215	0.479	0.254	0.860	0.076	0.809
Kalenjin ethnic group [c]	-0.858***	0.235	0.451*	0.259	0.497	0.523
Non-farm income from:						
Farm wage labour	0.000	0.000	-0.000***	0.000	-0.000**	0.000
Micro-businesses	0.000	0.000	0.000*	0.000	0.000	0.000
Formal employment	-0.000***	0.000	0.000***	0.000	0.000	0.000
Land rent	0.000	0.000	0.000	0.000	0.000**	0.000
Total land owned	0.017	0.014	0.000	0.012	-0.023	0.029
Household has child <2 years	-0.295	0.182	-0.401	0.383	-0.250*	0.151
Gender of household head	0.189**	0.085	-0.296	0.349	-0.525*	0.302
Farming experience	0.010	0.010				
Member of group in 2012	0.270***	0.097				
Resident in CSV	0.779***	0.092				
Household received forecast:						
On extreme weather occurrence	0.532***	0.168				
Three months in advance	0.357**	0.157				
Ten days in advance	-0.150	0.210				
Household perceives drought as cause of crop failure	-0.771*	0.460				
Amount of credit received	0.000	0.000				
Lagged asset index	0.031*	0.016				
Constant	1.209*	0.703	7.611***	1.231	7.633***	1.409
ln σ_A			0.637***	0.054		
$\rho_{A\varepsilon}$			-0.507*	0.292		
ln σ_N					0.722***	0.126
$\rho_{N\varepsilon}$					-0.531	0.674
Number of observations						407
Likelihood ratio test for independent equation x2						*3.09**
Log likelihood						*-1064.71*
F-statistics x^2						*0.000*

*The dependent variable is HDDS. These regime equations are jointly estimated with the selection equation: *, **, *** significant at the 10%, 5%, and 1% level, respectively: [a] Reference occupation is farming (crop/livestock); [b] Reference ethnic group is Luo*

Table 4. Adoption of improved multiple stress-tolerant crops and determinants of household domestic asset index

Independent variables	Improved multiple stress-tolerant crops adoption (1/0)		Determinants of household asset index			
			Adopters of improved multiple stress-tolerant crops		Non-adopters of improved multiple stress-tolerant crops	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	-0.006	0.009	0.002	0.007	-0.006	0.016
Primary education	-0.188	0.419	0.150	0.163	0.276	0.383
Secondary education	-0.263	0.350	0.241	0.151	0.463	0.460
Tertiary/college/university	-0.147	0.966	0.601**	0.287	0.428	1.131
Occupation of household head						
Farm wage employment	-0.409***	0.103	0.817**	0.383	0.439	0.276
Non-farm employment	0.171	0.222	0.108	0.269	-0.150	0.221
Micro-enterprise	0.001	0.127	0.341	0.211	0.138	0.135
Other employment	-0.512	0.454	0.760**	0.345	0.070	0.461
Gender of household head	0.220*	0.128	-0.121	0.105	0.359***	0.124
Non-farm income from:						
Farm wage labour	0.000	0.000	0.000	0.000	0.000	0.000
Micro-businesses	0.000	0.000	0.000*	0.000	0.000	0.000
Formal employment	-0.000***	0.000	0.000***	0.000	0.000***	0.000
Land rent	0.000	0.000	-0.000***	0.000	0.000	0.000
Credit received (KES)	0.000	0.000	0.000	0.000	0.000	0.000
Member of group in 2012	0.359***	0.128	-0.050	0.087	-0.183	0.120
Household size	-0.031	0.021	0.093***	0.020	0.054***	0.021
Farming experience	-0.003	0.015				
Resident in CSV	0.540***	0.133				
Household received forecast on:						
Extreme weather occurrence	0.436***	0.159				
Onset of rains	0.044	0.448				
Pest and diseases	0.162	0.101				
Lagged asset index	0.060***	0.014				
Kalenjin ethnic group [c]	-0.597***	0.214				
Constant	0.201	0.585	2.751***	0.520	1.707***	0.626
ln σ_A			-0.199*	0.109		
$\rho_{A\varepsilon}$			-0.865*	0.487		
ln σ_N					-0.041	0.652
$\rho_{N\varepsilon}$					-1.605	3.358
Number of observations						429
Likelihood ratio test for independent equation x2						3.16*
Log likelihood						-693.49
F-statistics x^2						0.000

*The dependent variable is log of domestic asset index. These regime equations are jointly estimated with the selection equation: *, **, *** significant at the 10%, 5%, and 1% level, respectively: [a] Reference occupation is farming (crop/livestock); [b] Reference household type is male headed with spouse; [c] Reference ethnic group is Luo*

Finally, we analyse impacts of improved multiple stress-tolerant crops on household income per adult equivalent. Results of this analyses are shown in Table 5, where we again confirm positive selection bias. Results at the lower segment of the table show a negative and significant covariance term for adopters of drought-tolerant crops.

As outlined, we also look at the post-estimation simulation of ATT, which is the central focus of our analyses. Results of these simulations are shown in Table 6 and show that uptake of improved multiple stress-tolerant crops have positive and significant influence, increasing diet diversity by a score of almost a factor of two. These findings differ substantially from the ones obtained via PSM and therefore confirm the presence of significant self-selection into adoption. We also evaluate impacts by village type (comparing impacts between CSVs and non-CSVs) and find that the observed difference between CSVs and non-CSVs are insignificant. Simulation of these impacts are based on a comparison group of non-adopters in the same locality. It is possible that non-adopters in CSVs may have realized spill-over effects of CSV activities. Analyses by poverty status of households also show that non-poor households tend to benefit more than poor households, however, the difference is again insignificant. The impact of improved multiple stress-tolerant crops on dietary diversity is not surprising, as it allows the households to produce diverse food crops on their farms. This improves access to more types of food, either because the farmers are able to produce them on their own or buy them from other farmers in the neighbourhood.

We undertake similar post-estimation simulation of impacts for asset index and these are shown in the middle segment of Table 6. The findings show that adoption of improved multiple stress-tolerant crops indeed has positive and significant impacts on asset accumulation. Adoption increases asset index by about 20 points. These estimates are indeed larger than PSM results (a maximum of 15 points increase in asset index), a clear indication of substantial positive selection bias.

Finally, we undertake post-estimation simulation of impacts for the income analyses, results of which are presented in the lower segment of Table 6. Our findings show that adoption of improved multiple stress-tolerant crops increases household income per adult equivalent by about KES 14,000 (approximately $137). Impacts are, however, larger for residents in non-CSVs (compared to CSVs) and non-poor households (compared to poor households). In all three cases, we find substantial deviations from the PSM results indicating presence of selection bias due to unobserved effects. Applying ESR, therefore, helps us eliminate the bias that would otherwise have been ignored if we relied purely on PSM analyses. The impact of improved multiple stress-tolerant crops on household income is consistent with our findings from KIIs, which indicated that the farmers sell off surplus produce to purchase other preferred food staples and household requirements.

Table 5. Adoption of improved multiple stress-tolerant crops and determinants of household income

Independent variables	Improved multiple stress -tolerant crops adoption (1/0)		Determinants of household income (per AE)			
			Adopters of improved multiple stress-tolerant crops		Non-adopters of improved multiple stress-tolerant crops	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	-0.012	0.013	-0.003	0.005	-0.004	0.005
Primary education	-0.149	0.112	0.275	0.294	0.084	0.248
Secondary education	-0.219	0.157	0.328	0.386	0.113	0.331
Tertiary/college/university	-0.018	0.360	0.573	0.507	0.215	0.296
Occupation of household head						
Farm wage employment	-0.522**	0.222	0.707*	0.397	0.238*	0.122
Non-farm employment	0.047	0.148	0.132	0.110	0.002	0.151
Micro-enterprise	0.076	0.171	0.400	0.464	0.221	0.155
Other employment	-0.291	0.556	-0.017	0.175	0.153	0.227
Gender of household head	0.233**	0.098	-0.088	0.174	0.104	0.127
Kalenjin ethnic group [c]	-0.792***	0.194	-0.518**	0.245	-0.239*	0.134
Credit received (KES)	0.000**	0.000	0.000	0.000	0.000**	0.000
Non-farm income from:						
Farm wage labour	0.000	0.000	0.000	0.000	0.000	0.000
Micro-businesses	0.000	0.000	-0.000*	0.000	0.000	0.000
Formal employment	-0.000***	0.000	0.000	0.000	0.000	0.000
Land rent	0.000	0.000	0.000	0.000	0.000***	0.000
Remittance	0.000	0.000	0.000***	0.000	0.000	0.000
Household size	-0.005	0.026	-0.026	0.019	-0.086***	0.028
Member of group in 2012	0.291**	0.126	-0.418***	0.088	-0.090	0.146
Resident in CSV	0.773***	0.111				
Farming experience	0.011	0.012				
Household received forecast on extreme weather	0.533***	0.181				
Household perception of causes of crop failure						
Drought	-0.874***	0.218				
Floods	-0.095	0.108				
Pests and diseases	0.214	0.168				
Lagged asset index	0.032**	0.015				
Constant	0.970**	0.495	11.660***	0.449	10.823***	0.403
ln σ_A			0.050	0.063		
$\rho_{A\varepsilon}$			-0.461*	0.261		
ln σ_N					-0.223	0.204
$\rho_{N\varepsilon}$					-0.263	0.210
Number of observations						413
Likelihood ratio test for independent equation x2						7.82***
Log likelihood						-774.82
F-statistics x^2						0.000

*The dependent variable is log of income per adult equivalent. These regime equations are jointly estimated with the selection equation: *, **, *** significant at the 10%, 5%, and 1% level, respectively: [a] Reference occupation is farming (crop/livestock); [b] Reference household type is male headed with spouse; [c] Reference ethnic group is Luo*

Table 6. Simulated impact of improved multiple stress-tolerant crop varieties on household dietary diversity, asset index and income by village type and household poverty status

	No. of obs.	Without adoption	With adoption	Net change
	Household dietary diversity score			
All adopters of improved multiple stress-tolerant crop varieties	202	5.700	7.326	1.626***
By village type [a]				
CSVs	134	6.001	7.434	1.433***
Non-CSVs	68	5.109	7.113	2.004***
By poverty status				
Extremely and moderately poor	141	5.821	7.304	1.483***
Non-poor	61	5.424	7.377	1.953***
	Domestic asset index			
All adopters of improved multiple stress-tolerant crop varieties	205	4.943	25.533	20.590***
By village type [a]				
CSVs	135	5.296	26.390	21.094***
Non-CSVs	70	4.323	23.951	19.628***
By poverty status				
Extremely and moderately poor	173	4.797	25.229	20.432***
Non-poor	32	5.818	27.113	21.295***
	Household income per adult equivalent (KES '000)			
All adopters of improved multiple stress-tolerant crop varieties	203	26.056	40.497	14.441***
By village type [a]				
CSVs	133	26.769	39.379	12.610**
Non-CSVs	70	24.711	42.702	17.991***
By poverty status				
Extremely and moderately poor	140	25.926	37.086	11.160**
Non-poor	63	26.318	49.217	22.899***

, **, * significant at the 10%, 5%, and 1% level, respectively.*
[a] *Note: there is no significant difference in net change in HDDS due to adoption between CSVs and non-CSVs, nor between poor and non-poor households; net change in asset index due to adoption between CSVs and non-CSVs is significant at 10%, but insignificant between poor and non-poor households.*

Adoption and impacts of improved and better adapted livestock on household dietary diversity score and asset index

We follow the same procedure as in the case of improved multiple stress-tolerant crops and apply ESR to evaluate impacts of improved and better adapted livestock on HDDS and asset index. Since our PSM analyses revealed that adoption of improved livestock has no significant effect on income we limit the ESR analyses to HDDS and asset index. First, we present results of the analyses for HDDS and the estimation results for ESR are presented in Table 7. Starting with the adoption component, we find that the Kalenjin ethnic community are more likely to adopt improved livestock breeds, possibly underscoring the value of livestock to this community. Similarly, male headed households are more likely to adopt improved livestock. This is probably due to general male dominance over asset ownership. We also find that income from off-farm sources positively influences adoption. Access to credit also encourages adoption of improved livestock. This confirms the role of credit in technology adoption. Finally, our analysis reveals that households tend to adopt improved livestock in response to unfavourable climatic conditions. This is confirmed by the positive and significant influence of forecast of extreme weather occurrence.

Turning to the regime estimations, we find evidence of individual heterogeneity as exemplified by the differential effects of the same variables between adopters and non-adopters. While education is important for both adopters and non-adopters, households whose head has tertiary education tend to have more diversified diets especially among households that have adopted improved livestock. This level of education has no significant effect among non-adopters. Instead primary and secondary education for household head significantly minimize diet diversity among non-adopters. Similarly, we find that among adopters of improved livestock, household heads' engagement in non-farm employment and micro-enterprises significantly reduces household dietary diversity. Interestingly, among non-adopters of improved livestock, engagement in micro-enterprises by household heads increases household dietary diversity. Finally, we find evidence of endogeneity, where households are self-selecting into adoption of improved livestock breeds due to unobserved effects. Significant dependence among selection and regime equations also confirms this. However, unlike in previous cases, we find that the correlation coefficient $\rho_{A\varepsilon}$ has a positive sign.

Our final ESR analyses looks at the impacts of improved livestock breeds on household asset index. Results for adoption of improved livestock breeds and determinants of respective outcomes are displayed in Tables 7 and 8 followed by the simulation of impacts, which is shown in Table 9. Adopters and non-adopters of improved livestock breeds are structurally different as indicated by the differential effects of similar variables on household asset index. For adopters, farm wage employment, income from farm wages and micro-enterprises positively influences wealth accumulation. For non-adopters of improved livestock, income from formal employment plays a positive and significant role. We, however, find no evidence of endogeneity.

As in the case of improved multiple stress-tolerant crops, we proceed with post-estimation simulation to understand the average effect of improved and better adapted livestock breeds for those who decide to adopt (ATT). Results of these simulations are displayed in Table 9 and show that uptake of improved and better adapted livestock has a positive effect on food security, increasing HDDS by a score of three on average. This is higher than what is achieved through uptake of improved multiple stress-tolerant crops. Comparison across village type and household poverty status shows no significant differences. We, however, note that there were more poor households among adopters of improved and better adapted livestock breeds. We also conduct post-estimation simulation of impacts for domestic asset index and these results are displayed in the lower segment of Table 9. We find that adoption of improved livestock breeds has positive and significant impacts on asset index. We also note that adopters in non-CSVs benefit significantly more than adopters in CSVs.

Table 7. Adoption of improved and better adapted livestock and determinants of household dietary diversity

Independent variables	Improved livestock adoption (1/0)		Determinants of household dietary diversity score			
			Adopters of improved livestock		Non-adopters of improved livestock	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	0.000	0.005	0.008	0.014	-0.011	0.008
Primary education	0.063	0.209	1.164	0.819	-1.027***	0.383
Secondary education	-0.024	0.295	1.187	1.172	-0.716*	0.383
Tertiary/college/university	0.414	0.389	3.088**	1.269	-0.939	0.803
Occupation of household head						
Farm wage employment	-0.318	0.248	0.156	0.915	2.109***	0.516
Non-farm employment	-0.050	0.257	-0.829*	0.438	-0.224	0.211
Micro-enterprise	-0.229	0.306	-1.355***	0.365	1.198***	0.331
Other employment	0.554	0.480	0.456	1.243	-0.069	0.601
Gender of household head	0.313**	0.135	-0.423	0.443	-0.458***	0.155
Kalenjin ethnic group [c]	0.392*	0.231	-0.288	0.522	0.217	0.402
Non-farm income from:						
Micro-businesses	0.000***	0.000	0.000	0.000	0.000	0.000
Formal employment	0.000*	0.000	0.000**	0.000	0.000	0.000
Land rent	0.000	0.000	0.000	0.000	0.000***	0.000
Household has child <2 years	-0.050	0.228	-0.482	0.382	-0.625**	0.258
Crop diversity (count)	0.126	0.084	0.131	0.163	0.262**	0.124
Household size	0.068***	0.026	0.128*	0.076	0.023	0.042
Credit received (KES)	0.000**	0.000				
Lagged livestock experience	-0.007	0.012				
Total land owned	0.008	0.020				
Farming experience	0.019	0.012				
Lagged group membership	-0.200*	0.111				
Resident in CSV	0.916***	0.299				
Household received forecast on:						
Extreme weather occurrence	0.505***	0.133				
Onset of rains	-0.451**	0.221				
Household perceive drought as cause of crop failure	-0.848***	0.242				
Lagged asset index	-0.003	0.002				
Constant	-2.433***	0.774	4.649*	2.392	7.194***	0.960
ln σ_A			0.535***	0.103		
$\rho_{A\varepsilon}$			0.593**	0.302		
ln σ_N					0.713***	0.092
$\rho_{N\varepsilon}$					-0.879	0.670
Number of observations						430
Likelihood ratio test for independent equation x2						6.49**
Log likelihood						-1039.66
F-statistics x^2						0.000

*The dependent variable is HDDS. These regime equations are jointly estimated with the selection equation: *, **, *** significant at the 10%, 5%, and 1% level, respectively: [a] Reference occupation is farming (crop/livestock) [b] Reference ethnic group is Luo*

Table 8. Adoption of improved and better adapted livestock and determinants of household domestic asset index

Independent variables	Improved livestock adoption (1/0)		Determinants of household asset index			
			Users of improved livestock		Non-users improved livestock	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	0.005	0.003	-0.013	0.009	-0.011	0.007
Primary education	-0.072	0.233	-0.406	0.498	0.277	0.230
Secondary education	-0.067	0.335	-0.218	0.490	0.367	0.262
Tertiary/college/university	0.028	0.543	-0.543	0.619	0.611	0.420
Total land owned	0.003	0.017	0.043*	0.024	0.026	0.026
Occupation of household head						
Farm wage employment	-0.501	0.643	0.711**	0.306	0.249	0.211
Non-farm employment	0.060	0.270	0.045	0.174	0.134	0.316
Micro-enterprise	-0.360	0.291	0.265	0.389	0.359	0.227
Other employment	-0.303	0.422	-0.446	0.288	-0.072	0.363
Gender of household head	0.318*	0.184	0.443	0.296	0.162	0.193
Non-farm income from:						
Farm wage employment	0.000	0.000	0.000	0.000	0.000	0.000
Micro-businesses	0.000**	0.000	0.000**	0.000	0.000	0.000
Formal employment	0.000	0.000	0.000	0.000	0.000**	0.000
Remittance	0.000	0.000	0.000	0.000	0.000	0.000
Credit received (KES)	0.000	0.000	0.000	0.000	0.000	0.000
Kalenjin ethnic group [c]	0.305**	0.129	-0.776***	0.159	-0.565***	0.129
Lagged group membership	0.119	0.143	0.115	0.113	0.170	0.133
Lagged livestock experience	-0.011*	0.006				
Farming experience	0.001	0.009				
Resident in CSV	0.676***	0.246				
Household received forecast on extreme weather occurrence	0.405**	0.188				
Constant	-2.077***	0.496	4.998***	0.960	3.296***	0.517
ln σ_A			-0.307***	0.09		
$\rho_{A\varepsilon}$			-0.374	0.377		
ln σ_N					-0.076	0.212
$\rho_{N\varepsilon}$					-1.657	1.748
Number of observations						384
Likelihood ratio test for independent equation x2						*2.06*
Log likelihood						*-604.09*
F-statistics x^2						*0.000*

*The dependent variable is log asset index. These regime equations are jointly estimated with the selection equation: *, **, *** significant at the 10%, 5%, and 1% level, respectively: [a] Reference occupation is farming (crop/livestock) [b] Reference ethnic group is Luo*

Table 9. Simulated impact of improved livestock breeds on household dietary diversity score and asset index by village type and household poverty status

	No. of obs.	Without adoption	With adoption	Net change
	Household dietary diversity score			
All adopters of improved livestock breed	91	4.700	7.594	2.9***
By village type [a]				
CSVs	72	4.887	7.564	2.7***
Non-CSVs	19	3.993	7.707	3.7***
By poverty status				
Extremely and moderately poor	69	4.675	7.494	2.8***
Non-poor	22	4.782	7.905	3.1***
	Domestic asset index			
All adopters of improved livestock breed	91	5.360	27.577	22.2***
By village type [a]				
CSVs	72	5.836	27.303	21.5***
Non-CSVs	19	3.885	28.617	24.7***
By poverty status				
Extremely and moderately poor	69	4.978	25.687	20.7***
Non-poor	22	6.746	34.364	27.6***

, **, * significant at the 10%, 5%, and 1% level, respectively.*
[a] *Note: difference in net change in HDDS due to adoption between CSVs and non-CSVs is significant at 1%, difference in impact between poor and non-poor households significant at 1%; net change in asset index due to adoption between CSVs and non-CSVs is significant at 1%, but insignificant between poor and non-poor households*

4. Conclusion and policy implications

Smallholder farmers in East Africa are disproportionately vulnerable to the impacts of climate change and climate variability, partly attributed to over-dependence on natural resources for livelihoods, poverty, and limited integration into markets. These farmers have always faced high rainfall variability within and between seasons, and the farming systems have been changing. Climate change is likely to reduce their crop yields and compromise incomes, food and nutritional security. While these farmers have been adjusting their farming practices to cope with climate variability and change using their limited resources and information, the scale of change will surpass the limits of local knowledge making their responses inadequate and unsustainable. Increasing agricultural productivity and meeting food security needs in the face of climate variability and change in East Africa, therefore, requires a range of technological, institutional and policy interventions. It is, therefore, important to identify approaches that would support ongoing initiatives by the farmers, communities and governments to enhance adaptive capacity and resilience of smallholder farmers in East Africa.

In order to build resilience and adaptive capacity of smallholders to climate change and to promote mitigation actions, CCAFS has been working with international and national research organizations, and NGOs since 2011 to test, evaluate, and increase access to and promote a portfolio of CSA technologies, practices and innovations appropriate to local agro-ecological conditions across CSVs in East Africa, with the aim of scaling appropriate options and drawing out lessons for policy makers across scales. Other support services include agro-advisories, coupled with direct linkages to input suppliers to improve access to inputs of high quality at affordable prices. Individual farmers and farmer groups are directly engaged in experimentation, selection and testing of the identified and appropriate CSA technologies and innovations that respond to the climate-related risks. In addition, farmers are trained to learn, through on-farm demonstrations and farmer fairs, to address agricultural production constraints and to inform policies at local (county, district) and national levels.

While M&E data showed progress on uptake of specific CSA technologies and practices from 2012, impact assessment to determine what works and what does not for programming and for policy decisions had not been undertaken. Besides, the M&E data were collected only for the participating households, and thus not suitable for impact assessment. This paper analysed uptake and impacts of the CSA technologies and practices—improved multiple stress-tolerant crop varieties, improved and better adapted livestock breeds and integrated soil and water conservation measures—on household food and nutritional security, incomes and asset accumulation, all of which are among the indicators of improved livelihood outcomes and resilience. Using cross-sectional data from the Nyando CSVs, including both project participants and non-participants for impact evaluation, the paper used a mix of quantitative and qualitative approaches combining household survey and KIIs. Specific indicators of livelihood outcomes and resilience included HDDS as a measure of food and nutritional security, household income per adult equivalent and household asset index.

The results show that adoption of CSA practices depend on household socio-economic factors and institutional variables. Improved multiple stress-tolerant varieties and improved and better adapted small ruminants had significant impact on livelihood outcomes. Farmers adopting multiple stress-tolerant crop varieties and improved and better adapted small ruminant livestock had access to more types of food and accumulated more household assets than the non-adopting households. Adoption of multiple stress-tolerant crop varieties increased income per adult equivalent by about $140. These results indicate that these CSA technologies are successful in helping households cope with climate risks and enhances adaptation to climate change and resilience of smallholder farmers. It is therefore important to promote wider uptake of these technologies across East Africa. The impact of integrated soil and water conservation practices were marginal and largely insignificant, therefore, not all the CSA practices and innovations being tested and promoted had significant positive impacts on household livelihood outcomes.

A key question is how these technologies can be effectively promoted within and beyond the CSVs (scaled up and out). To address this question, the study examined the drivers of adoption of CSA technologies and innovations. Adoption of CSA technologies, practices and innovations is location-specific. The lower regions of the Nyando, for example, showed higher likelihood of adopting improved multiple stress-tolerant crop varieties, while for the upper zones the likelihood of adopting improved and better adapted small ruminant livestock breeds was higher. This implies that culture, experiences and micro-climate are important in influencing farmer's choices of CSA technologies and practices, underscoring the importance of participatory action learning approaches used in the CSVs that takes local knowledge into consideration, for enhancing adaptive capacity of the farmers and their communities. Farmers have a lot to learn from each other, and as they learn, they are more likely to change their cultural orientation and accept new and proven CSA technologies. Thus, continuous learning through on-farm demonstrations, farmer fairs, and exchange visits are very important in accelerating adoption of CSA technologies and innovations. Also important is the need to evaluate local agro-ecological conditions in a participatory manner before a technology is replicated in areas exhibiting similar biophysical and socio-economic characteristics.

The results also show gender differences in adoption of CSA, where female farmers were more likely to adopt CSA technologies compared to their male counterparts. This is impressive because women, especially in rural environments are often disadvantaged. Thus, CSA technologies and practices can be a viable option for empowering rural women. For a quick and more effective way of building the adaptive capacity and resilience of communities, women should be primary targets. Working through women's groups or promoting gender equality at the farmer organization level to ensure that women are at the centre of efforts to build adaptive capacity are options which should be explored. Besides women, it is important to target people whose main occupation is farming rather than those for which agriculture is a secondary occupation and are unlikely to take up CSA technologies promptly.

Probability of adoption of CSA was higher for farmers who were members of farmer groups and those within the CSVs, farmers who anticipated occurrence of climate extremes, farmers who received weather forecasts three months before the planting time and wealthier farmers. Mobilizing smallholder farmers to work in groups, either to leverage on innovation funds or rotational farm labour is likely to increase uptake of CSA, and therefore justifies the approach of using farmer groups and CBOs as in the case of CSVs in East Africa. Groups enable farmers to build an asset base, allowing them to respond to climate change challenges. CSVs mobilize farmers, provide training and conduct participatory research, equipping farmers with the right knowledge and information to adapt to climate change. When farmers expect the occurrence of weather extremes, they are likely to take precautionary measures, hence they are more likely to take up adaptation measures. Because CSA adoption may be expensive, wealthier farmers are more likely to adapt. This is because the CSA technologies and complementary activities are not freely available. Thus, poor farmers may be locked out. The implications are that adaptation actions are better implemented through groups and CCAFS and stakeholders should continue to work with and strengthen the groups to work even better. Partnership with meteorological agencies should be enhanced to enable farmers to get up-to-date forecasts early enough for planning purposes. Lastly, poor farmers should be given special attention, either by giving them options that would strengthen their asset base or targeting them with the innovation fund.

Appendix 1: Extended explanation of the estimation strategy

A switching regression model assumes systematic differences between households that apply CSA interventions and the comparison groups that use non-CSA practices. This difference can be captured via the structure of equations below that assume that similar variables would have varying effects on outcome variables depending on whether one adopts the CSA technologies:

$$\begin{aligned} y_A &= X\beta_A + u_A \\ y_N &= X\beta_n + u_N \\ \\ I^* &= Z\alpha - \varepsilon \end{aligned} \qquad (3)$$

where y_A and y_N represent household outcomes (food security – household dietary diversity; asset index; income) for adopters of climate-smart interventions and non-adopters, respectively, and I^* is a latent variable determining which regime applies. β_a and β_N are sets of parameters to be estimated. While the variable sets $\boldsymbol{X}$ and $\boldsymbol{Z}$ are allowed to overlap, proper identification requires that at least one variable in *Z* does not appear in *X*. Note that in a cross-section sample y_{cs} and y_t are only partially observed: y_{cs} is only observed for the subsample of adopters of respective CSA interventions (drought-tolerant crop, improved livestock or soil and water conservation), and y_t for the subsample of households using conventional/traditional approaches. So, what is totally observed is a single variable y_i defined as follows:

$$y_i = \begin{cases} y_A & \text{if } I^* > 0 \\ y_N & \text{if } I^* \leq 0 \end{cases} \ \textit{and}\ I = \begin{cases} 1 & \text{if } I^* > 0 \\ 0 & \text{if } I^* \leq 0 \end{cases} \qquad (4)$$

In equation (3), u_A, u_N, and ε are residuals that are only contemporaneously correlated; they are assumed to be jointly normally distributed with a mean vector 0, and covariance matrix as follows:

$$\Sigma = \begin{pmatrix} \sigma_A^2 & \sigma_{AN} & \sigma_{A\varepsilon} \\ \sigma_{AN} & \sigma_N^2 & \sigma_{N\varepsilon} \\ \sigma_{A\varepsilon} & \sigma_{N\varepsilon} & \sigma_\varepsilon^2 \end{pmatrix} \qquad (5)$$

where $var(u_A) = \sigma_A^2$, $var(u_N) = \sigma_N^2$, $var(\varepsilon) = \sigma^2$, $cov(u_A, u_N) = \sigma_{AN}$, $cov(u_A, \varepsilon) = \sigma_{A\varepsilon}$, and $cov(u_N, \varepsilon) = \sigma_{N\varepsilon}$. The variance of ε is set to one, since α is estimable only up to a scale factor (Greene 2008, Maddala 1986). In addition, $\sigma_{AN} = 0$, since y_A and y_N are never observed together.

The switching model outlined so far accounts for observed systematic differences between adopters and non-adopters. When there are unobserved factors that matter, there will be correlation between the error terms of the regime equations and the selection equation. Estimates of the covariance terms can therefore provide a test for endogeneity. If $\sigma_{A\varepsilon} = \sigma_{N\varepsilon} = 0$, there is exogenous switching, but *if either $\sigma_{A\varepsilon}$ or $\sigma_{N\varepsilon}$ is non-zero, then we have a model with endogenous switching* (Maddala 1986). The test is achieved by testing for significance of the correlation coefficients between u_A and ε ($\rho_{A\varepsilon}$) computed as: $\sigma_{A\varepsilon}/\sigma_A\sigma_\varepsilon$ and, between u_N and ε ($\rho_{N\varepsilon}$) computed as: $\sigma_{N\varepsilon}/\sigma_N\sigma_\varepsilon$ (Lokshin and Sajaia 2004). Using these correlations, the expected values of the truncated error terms can be expressed as follows:

$$E(u_A|I = 1) = E(u_A|\varepsilon > Z\alpha) = -\sigma_{A\varepsilon}\frac{\emptyset(Z\alpha/\sigma)}{\phi(Z\alpha/\sigma)} = -\sigma_{A\varepsilon}\lambda_A \qquad (6)$$

$$E(u_N|I = 0) = E(u_N|\varepsilon \leq Z\alpha) = \sigma_{N\varepsilon}\frac{\emptyset(Z\alpha/\sigma)}{1-\phi(Z\alpha/\sigma)} = \sigma_{N\varepsilon}\lambda_N \qquad (7)$$

where $\emptyset$ and ϕ are the probability density and cumulative distribution function of the standard normal distribution, respectively. Hence, λ_A and λ_N are the Inverse Mills Ratios (IMR) evaluated at $Z\alpha$ (Greene, 2008).

Besides providing a test for endogeneity, the signs of covariance terms $\sigma_{A\varepsilon}$ and $\sigma_{N\varepsilon}$ have economic interpretation. If $\sigma_{A\varepsilon}$ and $\sigma_{N\varepsilon}$ have alternate signs, then households choose to adopt CSV interventions based on their comparative advantage (Fuglie and Bosch 1995, Maddala 1983). In other words, those who adopt have above average returns from adoption and those who do not adopt have above average returns from non-adoption. Alternatively, if $\sigma_{A\varepsilon}$ and $\sigma_{N\varepsilon}$ have the same sign, then there is evidence of "hierarchical sorting" (Fuglie and Bosch 1995), implying that adopters have above average food security status or incomes whether they adopt or not but are better off with adoption. Similarly, non-adopters have below average food security status or incomes whether they adopt or not but are better off not adopting. To this extent, the interpretation of the covariance terms also provides proof of model consistency, which requires that $\rho_{A\varepsilon} < \rho_{N\varepsilon}$ (Trost 1981). This condition also implies that adopters are better off with adoption than they would have been if they had not adopted.

Estimation procedure

When there is correlation between the error terms in equations (6) and (7), a two-stage method can be used to estimate the model. A first stage probit provides estimates of α, on which the IMRs can be calculated. The IMRs are then included in estimating the regime equations in (3) in the second stage and the resulting IMR coefficients provide estimates of $\sigma_{A\varepsilon}$ and $\sigma_{N\varepsilon}$. However, since the IMRs have been estimated, u_A and u_N cannot be used to calculate standard errors of the two-stage estimates (Fuglie and Bosch 1995, Maddala 1983).[5] A more efficient approach is the full information maximum likelihood (FIML) method for endogenous switching regression, which jointly estimates the selection and regime equations (Greene 2008, Lokshin and Sajaia 2004).

Note that the coefficients β_A and β_N in equation (3) measure the marginal effects of independent variables on household income/food security outcome *unconditional* on households' actual adoption, i.e. the potential effect of *X* on the respective subsample. If there are variables that appear both in *X* and *Z*, the coefficients can be used, however, to estimate conditional effects as follows:

$$\frac{\partial E(y_A|I=1)}{\partial X_j} = \beta_{Aj} - \alpha_j \sigma_{A\varepsilon} \frac{\phi(Z\alpha/\sigma)}{\Phi(Z\alpha/\sigma)} \left[Z\alpha/\sigma + \frac{\phi(Z\alpha/\sigma)}{\Phi(Z\alpha/\sigma)} \right] \qquad (8)$$

Equation (8) decomposes the effect of change in X_j into two parts: β_{Aj} is the direct effect on the mean of y_A ; the second part is the indirect effect from adoption that appears because of correlation between the unobserved component of y_A and I.

Estimating the effect of adoption on livelihood outcomes

To evaluate the income or food security effect of adoption of CSA interventions, we need to estimate the expected value of income/food security status that adopting households would have without adoption, otherwise known as conditional expectation (Maddala 1983). The evaluation proceeds as follows. First, for a household with characteristics *X* and *Z* who adopts a CSA intervention, the expected value of income/food security is:

$$E(y_A|I=1) = X\beta_A - \sigma_{A\varepsilon}\lambda_A \qquad (9)$$

where the last term considers sample selectivity i.e. that adopting households may behave differently from an average household with characteristics (*X* and *Z*) due to unobserved factors (Fuglie and Bosch

[5] A procedure for deriving consistent standard errors is provided by Maddala (1983, pp. 223-228), but the adjustment is quite cumbersome because the correct variance-covariance matrix of the estimates is complicated (Lee 1978).

1995). For the same adopter with the same characteristics X and Z, the expected income/food security had he chosen not to adopt would be (Maddala 1983, pp. 257-260):

$$E(y_N|I = 1) = X\beta_N - \sigma_{N\varepsilon}\lambda_A \tag{10}$$

The change in income or food security indicator due to adoption of the technologies can then be calculated as (Fuglie and Bosch 1995, Maddala 1983):

$$E(y_A|I = 1) - E(y_N|I = 1) = X(\beta_A - \beta_N) + (\sigma_{N\varepsilon} - \sigma_{A\varepsilon})\lambda_A \tag{11}$$

In the impact assessment literature, this is the ATT. By assuming the same characteristics, we hold constant all other possible causes of income differences.[6] The predicted difference in income represented by equation (11) is therefore due to the differences in coefficients in (9) and (10). If self-selection is based on comparative advantage, $\sigma_{N\varepsilon} - \sigma_{A\varepsilon}$ would be greater than zero, and adopting CSA interventions would produce bigger benefits under self-selection than under random assignment (Maddala 1983). Furthermore, simple comparison of mean outcomes of adopters and non-adopters, i.e. $E(y_A|I = 1)$ versus $E(y_N|I = 0)$ would lead to an upward or downward biased estimate of treatment effect depending on the signs of the covariance terms (Maddala 1983, p 260).

[6] Note that the unobserved factors are not ignored since λ_s remains in both equations (9) and (10). The procedure simply implies that the unobserved factors have different effects depending on which regime applies. By holding λ_s constant and taking the differences in effects $(\sigma_{tv} - \sigma_{sv})$, we partial out effects of unobserved factors so that the estimated difference in income is purely due to market channels, devoid of any unobserved effects.

Appendix 2: Indicators of covariate balancing before and after matching

Table 2a. Indicators of covariate balancing before and after matching

Matching algorithm	Outcome	Median absolute bias (before matching)	Median absolute bias (after matching)	% bias reduction	Pseudo R (unmatched)	Pseudo R (matched)	p-value of LR (unmatched)	p-value of LR (matched)
Improved and multiple stress-tolerant crop varieties								
Nearest neighbour	HDDS	14.3	5.3	62.9	0.17	0.03	0.000	0.519
	Domestic asset index	18.5	6.1	67.0	0.15	0.01	0.000	0.895
	Household income	11.6	7.4	36.2	0.16	0.04	0.000	0.204
Kernel	HDDS	14.3	2.6	81.8	0.17	0.01	0.000	0.965
	Domestic asset index	18.5	2.8	84.9	0.15	0.00	0.000	1.000
	Household income	14.3	7.7	46.2	0.18	0.03	0.000	0.670
Improved and better adapted small ruminants								
Nearest neighbour	HDDS	18.7	12.0	35.8	0.15	0.07	0.000	0.199
	Domestic asset index	19.5	12.3	36.9	0.14	0.06	0.000	0.277
	Household income	18.6	4.3	76.9	0.13	0.01	0.000	0.935
Kernel	HDDS	18.7	5.6	70.0	0.15	0.01	0.000	1.000
	Domestic asset index	18.4	4.0	78.3	0.15	0.01	0.000	1.000
	Household income	18.6	4.8	74.2	0.13	0.01	0.000	0.999
Integrated soil and water conservation								
Nearest neighbour	HDDS	10.6	8.5	19.8	0.10	0.04	0.000	0.253
	Domestic asset index	10.2	6.1	40.2	0.11	0.03	0.000	0.424
	Household income	10.2	4.1	59.8	0.12	0.02	0.000	0.973
Kernel	HDDS	10.6	3.1	70.8	0.10	0.01	0.000	1.000
	Domestic asset index	10.2	2.7	73.5	0.11	0.01	0.000	0.999
	Household income	10.2	2.4	76.5	0.12	0.01	0.000	1.000

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