Climate-smart agriculture is good for business

A framework for establishing the business case for climate-smart agriculture investments

Working Paper No. 316

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

Andreea C. Nowak
Peter Steward
Nictor Namoi
Megan Mayzelle
Hannah Kamau
Christine Lamanna
Todd S. Rosenstock

CGIAR

RESEARCH PROGRAM ON
Climate Change, Agriculture and Food Security

CCAFS

Working Paper

Climate-smart agriculture is good for business

A framework for establishing the business case for climate-smart agriculture investments

Working Paper No. 316

CGIAR Research Program on Climate Change,

Agriculture and Food Security (CCAFS)

Andreea C. Nowak
Peter Steward
Nictor Namoi
Megan Mayzelle
Hannah Kamau
Christine Lamanna
Todd S. Rosenstock

Correct citation:
Nowak AC, Steward P, Namoi N, Mayzelle M, Kamau H, Lamanna C, Rosenstock TS. 2020. Climate-smart agriculture is good for business. A framework for establishing the business case for climate-smart agriculture investments. CCAFS Working Paper no. 316. Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Titles in this series aim to disseminate interim climate change, agriculture and food security research and practices and stimulate feedback from the scientific community.

The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) is led by the International Center for Tropical Agriculture (CIAT) and carried out with support from the CGIAR Trust Fund and through bilateral funding agreements. For more information, please visit https://ccafs.cgiar.org/donors.

Contact:
CCAFS Program Management Unit, Wageningen University & Research, Lumen building, Droevendaalsesteeg 3a, 6708 PB Wageningen, the Netherlands. Email: ccafs@cgiar.org

Abstract

Climate-smart agriculture (CSA) makes financial sense for businesses. Governments are increasingly holding the private sector responsible for their role in climate change impacts. Extreme weather events are incredibly costly for businesses. This is particularly true in agriculture, which relies heavily on favorable weather conditions. CSA practices and technologies are central to the transformative changes necessary to maintain the stability—and profitability—of the food system in the face of climate change. Where robust information on the benefits, costs, and risks of interventions is missing or incomplete, would-be investors, including donors, governments, businesses, and farmers, remain uninformed of the potentially massive dividends climate-smart investments could offer. This dearth of viable business models ultimately hinders the mainstreaming of productive, climate-resilient, low-emissions agriculture. Robust business-case analyses of CSA could accelerate the scaling of promising, profitable technologies by transparently and rigorously laying out the monetary and non-monetary values of performance. We use existing data from *Evidence for Resilient Agriculture* (ERA, previously known as *The Compendium*) to develop a general framework for establishing the business case for specific farm-level agricultural technologies. The framework focuses on the costs, benefits, and risks of adoption of CSA by smallholder farmers. We illustrate the application of the framework with two case studies in Kenya and Malawi to highlight opportunities, challenges, and lessons learned from building business cases for CSA. These give potential investors the tools to screen and select appropriate technologies and help de-risk investments where data are few and far between.

Keywords

Climate change; Agriculture; Resilience; Business; Profitability; Risks

About the authors

Andreea C. Nowak is a research associate at the International Center for Forestry Research-World Agroforestry (CIFOR-ICRAF) based in Colombia. She conducts research on agriculture and climate change and is interested in innovation and science-communication techniques that bring data to life and help create meaningful, decision-oriented narratives. She holds an MSc in International Development and Management and a BA in Political Science.

Peter Steward is an PhD ecologist (University of Leeds) and CIFOR-ICRAF associate scientist for the CCAFS Evidence for Resilience Agriculture (ERA) project. He has a breadth of scientific experience in areas such as agricultural and conservation ecology, measurement of biodiversity and regulating ecosystem services, human wildlife conflict, agronomic trials for sustainable agriculture, crop-climate suitability modelling, advanced meta-analysis, agricultural ontologies and concept schemes, niche modelling, and prediction of outcome performance using machine learning.

Nictor Namoi is a research fellow at CIFOR-ICRAF in Nairobi, Kenya. He has worked extensively on ERA and on measurement of greenhouse gas emissions from soils. He has a Master of Science from the University of Nairobi and is currently pursuing a doctorate degree in sustainable farming systems.

Megan Mayzelle is a full-time freelance science writer. She has worked extensively in information communication technologies for agricultural development, national climate change programmatic planning, grant writing, and crop-livestock integrated systems. She holds degrees in International Agricultural Development and Soils and Biogeochemistry.

Hannah Kamau is a research associate at CIFOR-ICRAF in Nairobi, Kenya. She works on County climate-smart adaptation planning and ERA.

Christine Lamanna is a climate change ecologist with CIFOR-ICRAF in Nairobi, Kenya. She works primarily on climate change adaptation options for smallholder farmers in Africa.

Todd Rosenstock is a senior scientist with CIFOR-ICRAF based in Nairobi, Kenya. He investigates how smallholder farmers affect climate and vice versa. Methods development for monitoring social and environmental change are integral themes of his current work. He co-leads the CCAFS Low Emission Development SAMPLES among other programs. Todd is particularly interested in finding ways to link science with policy and programming.

Acknowledgements

This Working Paper was produced with the financial support of the United States Department of Agriculture-Foreign Agricultural Service (USDA-FAS) to operationalize CSA in Kenya and Malawi and the EU–IFAD project "Building Livelihoods and Resilience to Climate Change in East and West Africa: Agricultural Research for Development (AR4D) for large-scale implementation of Climate-Smart Agriculture" (#2000002575. Its contents are the sole responsibility of ICRAF and do not necessarily reflect the views of the funders. The work was implemented under the Partnership for Scaling Climate-Smart Agriculture (P4S) project that is co-led by ICRAF and the International Centre for Tropical Agriculture (CIAT) as part of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Contents

Acronyms

BAU	Business-as-usual
BCR	Benefit-cost ratio
CBA	Cost-benefit analysis
CF	Cash flow
CSA	Climate-smart agriculture
CV	Coefficient of variation
EB	Enterprise budget
ERA	Evidence for Resilient Agriculture
FC	Fixed costs
GI	Gross income
GM	Gross margins
ICRAF	World Agroforestry Centre
LC	Labor costs
LCL	Lower confidence limit
NPV	Net present value
NR	Net returns
PP	Payback period
RoFP	Returns to factors of production
RoI	Return on investment
SDG	Sustainable Development Goal
USDA-FAS	United States Department of Agriculture-Foreign Agriculture Service
VC	Variable costs
Yd	Yield dent

Introduction

Food production drives climate change. Agricultural production alone contributes nearly a quarter of global greenhouse gas emissions [1] and accounts for 80-86% of whole food system emissions [2], [3]. At the same time, agriculture, and particularly smallholder[1] tropical agriculture, which produces 30-34% of the world's food supply on 28-31% of the total agricultural land [4], is more vulnerable to climate impacts than any other sector. As climate change progresses, increasingly high temperatures, unpredictable precipitation, and extreme events will make it even more difficult for these farmers to produce food in sustainable, economically viable ways [5]. In eastern Africa, for example, maize production could decline by as much as 45% by the end of the century under the status quo [6]. Transformation of conventional agricultural production systems is needed [7], [8]; agriculture can no longer simply produce food; it must also protect the natural resources on which it relies and promote human and economic development. Balancing these outcomes in the face of climate change has become the challenge of the century [9].

Climate-smart agriculture (CSA) includes any farm- or landscape-level agricultural practice or technology, whether traditional or innovative, that builds in adaptation to weather variability and climate change while sustainably increasing food productivity and, where possible, supporting mitigation of greenhouse gas emissions [10]. Many field-level management technologies are climate-smart, ranging from drought-resistant seed varieties to improved livestock feeds, and from integrated soil and water management to agroforestry. The effectiveness of CSA practices across time scales and agroecological zones is supported by abundant scientific evidence. That said, the most effective suite of CSA practices for any given farm will vary with crop type, geography, and cultures, among many other factors [11]–[13].

Moving toward CSA practices is part of the transformation needed to maintain/increase agricultural productivity in environmentally sustainable and economically viable ways [11]. Yet in spite of the seemingly apparent advantages of CSA[12]–[15], the move toward an agricultural transformation is largely unrealized, despite hundreds of millions of US dollars in public funding invested in evidence generation and knowledge creation. This is exacerbated by the fact that CSA is not a silver bullet, but rather a suite of potential interventions that must be tailored to each farm's unique circumstances. As such, the barriers to change are myriad and frequently unique to each individual farm [16]–[19].

[1] Smallholder agriculture is herein defined by land size, i.e., farms smaller than 2 hectares.

Ultimately, the adoption of CSA practices sits with farmers, and relies on smart information (relevant and timely) that leads to smart decisions (carefully weighing risks). Like most private sector enterprises, farmers manage resources to optimize performance and meet objectives. For tropical smallholders, the vast majority of whom live in poverty, objectives tend to focus on immediate needs, not medium- to long-term investments. These farmers frequently understand the benefits of CSA in terms of maximizing profits, minimizing potential losses, stabilizing production, minimizing costs, and diversifying outputs, and simply lack secure access to land, labor, and capital to do so without putting their families' immediate wellbeing at risk.

This represents a clear opportunity to stimulate adoption and investment through private sector approaches, and there has indeed been a recent shift toward the same [20], [21]. Nevertheless, most key actors in the space remain uninformed or wary of the economics of agricultural transformations. This ultimately hinders the mainstreaming of productive, climate-resilient, low-emissions agriculture. The first step toward effectively supporting and fostering this new approach is to establish the business case for climate-smart investments.

Business cases are widely applied in various fields, including financial planning and forecasting, project management, enterprise, and compliance reporting. They are developed to quantify impacts, provide analysis to support and justify selection of specific options and create impetus to take action. In the context of agricultural development, a business case allows investors at different levels—governments, development partners, the private sector and farmers—to anticipate the profitability, riskiness, and societal value of investments in order to strategically allocate resources for optimum impact. The business case for CSA can be particularly high-impact in the context of small-holder farmers, who rely heavily on climate, have limited access to lucrative markets, and tend to be more risk-averse, inhibiting their adoption of climate-smart technologies. Laying out how CSA can be good for farm businesses can have a transformative role for more than 500 million farmers that practice small-scale agriculture worldwide.

The scientific community can have an important contribution in the way farm profitability and risk information is communicated, leveraging knowledge from different disciplines and existing farm datasets. In this paper, we present a framework for establishing the business case for CSA, distilling key elements that help highlight CSA as an attractive business model for investors at all levels. To date, few, if any, research efforts have systematically aggregated and communicated the potential profitability of climate-smart investments in practical information ready to be used by the investment community. This paper fills this gap; it draws on agricultural management and economics literature and practice to highlight relevant approaches to assessing benefits, costs, and risks associated with climate-smart investments and suggests a frame for organizing these ideas in a succinct, “marketable” format to be used by non-scientific audiences. It also highlights opportunities to leverage existing data for generating new analyses and actionable messages. By doing so, the framework is intended to guide investors, development practitioners and researchers as they seek to create viable business models for de-risking agriculture and take CSA to scale.

We first present a guiding framework for establishing the business case for climate-smart investments, including detailed accounts of the scope, data types, and methods for data compilation, aggregation, and analysis. Rather than offering a checklist of themes and indicators that a business case for CSA should contain, the framework lays out key considerations for analyzing smallholder farm profitability from several angles. The extent to which these considerations are included in any given business case will depend on its specific objectives. Second, we illustrate key methodological insights and lessons learned from implementing the framework using data from the Evidence for Resilience Agriculture (ERA)[2] database. Finally, we offer lessons learned from this effort. This working paper is the first of its kind, and we hope it will further catalyze the ongoing dialogue between farmers, scientists, practitioners, and investors and inform the transition to a climate-smart future.

Setting the scope

Clearly articulating the boundaries of the business case (what is in and out of the scope) helps guide the selection of relevant data required for carrying out subsequent analyses. There are many dimensions to take into account in the scope setting stage. These may refer to the type of farming system considered, the type(s) of investment(s) analyzed, and thematic areas, among others.

In general, as the degree of specificity of a business case increases, so does the amount of information, analysis capacity and effort required. As such, the case specificity should be aligned with the scope of the assessment, the degree of detail required for the investment decision, and with the availability of relevant accurate data. For example, a business case for CSA may be designed around broader categories of practices/technologies (*e.g.*, crop management, soil management, agroforestry) or specific practices/technologies (*e.g.*, crop rotations, improved varieties, use of organic fertilizer, etc.); it may also offer granular information that adds context-specificity (*e.g.*, rotating maize with cowpea, alleycropping maize

[2] ERA aggregates over a hundred agricultural management technologies into standardized management categories: agroforestry, crop, livestock, soil, genetic, nutrient, water, energy, and post-harvest, as well as combinations of these (*e.g.*, agroforestry + nutrient, soil + nutrient + crop). The online database at https://era.ccafs.cgiar.org allows for tailoring of data granularity according to data needs.

and Gliricidia trees, drought tolerant varieties, etc.). Likewise, a business case may disaggregate information by agroecological zone (AEZ[3]) to compare performance or account for variations across distinct land, soil, and climate characteristics. While higher levels of aggregation create value to investors who seek to obtain swift snapshots of investment performance in general, more granular information can offer deeper insights into the particularities, the *why* and the *how* of investment performance.

A business case for CSA looks at investment opportunities from different themes (or subject matters), depending on their relevance for the CSA practice/technology and the investor's objective(s). Specific themes are relevant to specific investors and uses (See Tables 1-2). The themes selected will inform the variables to use in the analysis and may include farm profitability and risks, such as total expenditures, net returns, cost variability, and yields, among others, allowing investors to evaluate the associated opportunities and liabilities. The business case may also expand its thematic scope, and include a focus on areas of critical importance to society and the environment, such as the sustainable development goals (SDGs) [22], specifically those referring to poverty reduction, food security, nutrition, biodiversity protection, and land restoration, among others. This approach is particularly important for understanding the underlying causes of risks, as it helps identify farmers' capabilities and capacities, which, in turn, create risks of different types and degrees.

Data

A critical condition for developing a business case for CSA is data availability and quality. Sufficient and reliable information is a prerequisite to showcasing a compelling story and to designing holistic approaches to risk management. Availability of time-series data is critical for exploring how reliable or consistent technology or practice outcomes are between growing seasons. This can be measured, for example, using statistics such as yield stability (a proxy for production risks). If yields are unstable over time this suggests that production is susceptible to environmental stresses or shocks such as bad weather (droughts, high temperatures, storms, etc.) or pest and diseases. As such producers may require capacity to absorb losses in the bad years, this often very difficult for low income households.

Additionally, having temporally explicit data is improves the quality of economic statistics when synthesized from multiple publications. For example, cost-benefit ratio calculation combines

[3] AEZ-specific analyses have played an important role in land use planning, design, and promotion of context-specific crop/livestock adaptation and vulnerability-reduction options since the AEZ concept was developed by FAO in the late 1990s [55].

both benefit (income, employment, etc.) and cost (variable costs, fixed costs, etc.) data; matching the denominator and numerator for time of observation will reduces nuisance variance increasing the signal to noise ratio and providing stronger comparisons and conclusions.

The quality of data reported is also critical for ensuring value (relevance, usefulness) of the business case. Good quality data can help investors take informed decisions. Quality may refer to aspects of data accuracy, relevance, completeness, and consistency. For instance, when multiple investment cases (practices/technologies) are considered, the data needs to be consistently reported across investments, otherwise investments cannot be compared.

Tables 1 and 2 present a selection of proxies for investment profitability and riskiness in the context of CSA, with examples of how each has most often been used. The lists are non-exhaustive. Any given business case would use the most relevant proxies based on the particular context and taking into account aspects data availability and quality. Additional criteria for indicator selection may include: (i) relevance, meaning that it needs to meet the data needs of a certain user group (farm, service provider, policy-maker, etc.), (ii) specificity, meaning that the indicator addresses a dimension of a CSA investment rather than any farm practice; (iii) feasibility, defined as reasonable and affordable data collection; (iv) credibility, meaning that the indicator upholds scientific standards and is trusted by scientists and practitioners; and (v) usefulness, meaning that the indicator captures information that moves investments forward.

Indicators presented in Tables 1-2 are not mutually exclusive. Rather, they synergistically build a depth of perspective by analyzing overlapping sets of variables from different angles and degrees of specificity. For instance, Net Present Value (NPV) is based on estimates of investment costs, discount rates[4], and projected returns, and thus does not account for unforeseen expenditures. Returns on Investment (ROI) offers a slightly different perspective by considering total costs but without accounting for the time period when the costs and benefits will occur. Similarly, there is no agreed upon method for integrating these indicators into an overall evaluation of potential farm profits and risks. Rather, they are meant to be leveraged to create a multi-dimensional model of the potential economic performance, risks, and barriers of a CSA intervention.

[4] Discounting is important because the value of benefits and costs now are not the same as benefits and costs in the future and because, in many investment cases, benefits occur in the future, while costs occur at the beginning.

Economic performance

Farmers are private actors keen on maximizing profits with available resources. They seek to anticipate the costs and benefits of various agricultural management options and choose the most viable one(s) in terms of their needs. Having economic and financial information can help farmers make more informed decisions on e.g., minimum sale prices required to cover variable costs or make additional investments. For credit and insurance service providers, such information can provide valuable insights into actual farming risks; in the absence of this information, service providers tend to overestimate the riskiness of agricultural endeavors. Data on real risk enables service providers to tailor products to farmers' needs (e.g., small, frequent cash advances) as well as their own. For extension workers, farm data supports strategic use of resources to maximize the impact of productivity programming. Farm data also enable policymakers to consider how to tailor e.g. price and market regulations to benefit smallholder farmers.

A common way to quantify the monetary value and estimate the profitability of agricultural investments is a cost-benefit analysis (CBA) [23]–[25]. CBAs calculate the net economic effects of agricultural investments with and without the investment (not before and after an intervention). A CBA can be carried out at different stages of an intervention, including ex-ante (to guide design and implementation), medium-term (for monitoring progress) and ex-post (to quantify results, successes, and failures). Key indicators included in a CBA are NPV and Benefit-Cost Ratio (BCR), explained in Table 1. CBAs have recently been used to estimate the profitability of various soil and water technologies across Africa, Central America, and Asia [26], [27]. When resources for conducting CBAs are limited or when the scope, there are alternative options to look at the riskiness and profitability of an investment, such as costs, margins or social returns on investments (SROI), as illustrated in Table 1.

Table 1. Examples of proxies for economic performance and farm profitability, organized by their level of complexity (from simpler to more complex)

Indicator	Definition and relevance to CSA investments	Calculation/ common formula	Interpretation/ use
Fixed cost (FC) (value per ha)	• Cost borne by investors independent of the level of production. FCs are related to the operation of the business and may include rent, taxes, telephone, depreciation[5], among others. • FC typically represent 60% of total costs in agricultural enterprises and are more common for commercial farmers.	Sum of all fixed costs divided by total land area (in ha)	• Should be interpreted in conjunction with the farm revenue. • When FCs equal gross margins (see below), the breakeven point is reached, meaning that there are no profits and no losses. • Year 1 often has high FCs due to initial investments in materials, equipment, etc. but are offset by benefits in subsequent years. • Higher FCs in the production stage means more business risk, especially when revenues are hard to anticipate (volatile prices).
Variable cost (VC) (value per ha)	• Cost that varies with production, i.e., it increases when production goes up and decrease when production falls. • VCs include inputs purchased, seasonal labor, fuel, livestock feed, vaccines, etc. • VCs typically represent 40% of total costs in agricultural enterprises. • Most costs incurred by smallholder farmers are VCs.	Total VC = cost to make product x nr. of units produced	• Should to be interpreted in conjunction with the farm revenue. • Business losses occur when gross profits are lower than VCs. • Decisions on VCs (e.g., input use) influence profitability. • In general, an investor seeks to change the cost structure and turn some of the VCs into one-time costs. However, in reality, farmers decide on input use way ahead of having information on yields, product quality and prices, which makes VC optimization difficult.
Labor cost (LC) (value per ha or per activity)	• Cost of labor engaged in the farm activities required by the investment. This includes both family and hired labor. • LC vary across seasons and farm activities (land preparation, weeding, harvesting) and may be variable (e.g., seasonal labor) or fixed (e.g., hired labor to maintain the operation). • Ideally, labor data should be disaggregated by activities to give a better picture of labor productivity at different times (seasons) and in different activities required by the investment.	Common formulas: LC= number of hired person-day per activity x wage rate for each activity LC= number of hired person-day per hectare per activity x wage rate for each activity LC= total person-days x wage rate for each day	• High labor costs can represent an investment risk and therefore a disincentive to invest in the farm practice, especially where farm labor is in short supply (due to illness, migration to urban areas, etc.) and when the practice is labor-demanding.
Return to factors of production (RoFP) (yield per unit of labor or ha)	• The change in output when an additional unit of a given input or factor of production (*e.g.*, labor, capital, natural resources) is added and all other factors are held constant. • RoFP helps estimate the optimum input efficiency.	For returns to labor (RoL): RoL = (Total income – VC)/ Total labor days)	• Needs to be interpreted closely with the initial investment costs. • Even if some farm investments may be attractive in terms of yield per unit of labor/land, this requires farmers to make an initial investment ahead of reaping the benefits, which is not always attractive for farmers lacking the initial capital.

[5] Depreciation represents the costs of the declining value of machinery, farm assets (tractors), etc, typically calculated as an annual cost.

Gross income (GI) (or value of output) (value per ha)	• Sum of all cash (derived from product sales) and non-cash returns (product consumed in the household or stored). • GI can be determined irrespective of the amount of the product that is being sold, consumed or stored. However, insights into amount of product consumed/stored or of by-product can provide a deeper understanding of the farm's sources of income. • GI is different for annual and perennial crop systems.	GI = yield x farmgate price (the first selling point) When the farmgate price is unknown, this is typically replaced with information on transportation or marketing costs.	• GI is used as an estimate of farm income but not of profitability (as it does not include insights on costs). • GI is typically used as basis for further calculations of other farm-level financial indicators (see below Gross Margins)
Gross margin (GM)[6] (value per ha, per worker or per person day)	• The difference between gross farm income and VCs. • GM is not equal to profit, as it does not account for FC. • However, it is still a relevant and easy to use tool, as its calculations are straightforward and allows valuing non-purchased inputs such as family labor, manure, draft power, etc. (variable costs).	GM = GI - VC	• GM is an indication of the production and economic efficiency of the farm enterprise. Positive GM indicates profitability. An increase in GM means an increase in profit, as FCs do not vary with production. • GM is a planning tool particularly relevant for smallholder farmers (whose FCs are minimal) and for comparing performance of different practices and technologies or two different investments with similar fixed cost structures and similar unit basis (e.g., hectare, labor).
Net returns (NR) (net income) (value per ha)	• Accounts for total costs (TC), including FCs (depreciation, permanent labor, and other farm operating costs)	NR = GR – TC , where TC= total costs (sum of all FCs and VCs)	• An indication of investment profitability and riskiness. • Negative net returns indicate losses. Consecutive years of losses suggest the net income is insufficient to cover expenditures.
Cash flow (CF) (or liquidity) (value)	• The amount of cash and assets available to pay for costs in the future. Liquidity is particularly important to farmers for running daily farm operations. • Inflow and outflow of cash varies throughout the year, which is why cash flow analyses need to be considered monthly or quarterly. • Unlike profitability, which typically focuses on business success on the long run, liquidity indicates the ease with which short-term financial obligations can be met.	CF = Cash inflows – cash outflows , where cash inflows = money received from the sale of farm produce; cash outflows = money paid out for inputs and materials	• CF does not equal profitability. It is an indication that a farm investment may/may not be viable as it does not generate sufficient cash to cover needs.
Returns on investment (ROI) (ratio)	• A cash flow measure that evaluates the financial value (or the benefits) the farmer receives relative to investment cost over a given period of time. It is expressed as a ratio between the gain (or loss) and the total costs (TC) associated with the investment.	Multiple formulas: ROI = NR / TC or %ROI = (Total benefits – TC) / TC	• ROI is typically correlated with risks, meaning that higher returns attract higher possible risks. • A positive ROI suggests profitability, while negative values indicate net loss (costs exceeding gains). • However, for the smallholder farmer, higher ROI does not necessarily mean a viable investment option if the benefits are

[6] GI and GM are usually calculated at the end of the cropping season or calendar year. For perennial crops, yields and prices likely vary during the year. If more than 2 types of cropping systems are being included in the analysis (e.g., perennial and annual), the calculations should be done for a given crop year (the same year(s) across all variables).

	• ROI does not account for the factor of time, which stymies comparison between investments with different amounts of time to recover the costs. Therefore, when making comparisons of investments under different time periods, investors opt for the annualized ROI (AROI). • ROI is a purely financial metric and does not account for social or environmental benefits and costs. A common alternative is the Social Return on Investment (SROI) [28], [29], which shows the value of each dollar invested to the individual and society.		reaped on the long run. Therefore, ROI is usually interpreted in conjunction with other metrics, such as payback period (See below).
Payback period (PP) (number)	• The length of time required for an investment to pay for itself (or to recoup money invested), expressed in numbers of days, weeks, months, seasons, years.	PP = Initial investment / Net cash flow per period	• In uncertain contexts (climate, market, socio-political), investments with shorter PPs are usually more attractive to smallholders, while longer PPs are riskier. • PP allows investors to make quick judgements on an investment, but it does not account for the time-value of money (i.e., the point in time when benefits may occur).
Net present value (NPV) (number)	• A cash flow measure often used as a component of a CBA, representing the multiple-year sum of the discounted net economic effects (value of benefits – value of costs). • NPV shows the economic viability of the investment (how much the investment will earn in present value terms) when the private/social discount rate factored is included. • Unlike ROI, it accounts for the time-value of money (i.e., when the benefits and costs occur), allowing comparisons against investment options.	NPV = NR x [1- (1+ i) ^ -n] / i – Initial Investment , where: NR = net returns (or cash flow) expected to be received in each period; i = the required rate of return per period (or the discount rate); n = the number of periods during which the investment is expected to operate and generate cash inflows.	• Values above 0 indicate that, when the effect of time is included in the calculation of the value of money, the projected earnings (*i.e.*, benefits) exceed anticipated costs. • A negative NPV indicates net loss. • Like ROI, the metric should be interpreted together with other measures of economic riskiness, such as costs or payback period.
Benefit-cost ratio (BCR) (ratio)	• Indicator used in CBA, revealing the overall value for money of an investment. It is calculated as the ratio between the benefits discounted over time (revenue, additional yield, labor savings, reduced soil erosion, *etc.*) and the costs of the investment discounted over time (*e.g.*, equipment, land, depreciation, water loss, *etc.*).	BCR = PV(B) / PV(C) , where: PV= Present value B= Benefits C= Costs	• A BCR greater than 1 indicates that benefits outweigh costs. • Costs and benefits occur at different times of the investment and typically follow a pattern in which costs are higher in the early phase of the investment and benefits are higher in the later phases. • Ratios may be misleading when comparing two investments with different costs and costs structures.

Risks

One way to define risk is to describe or quantify poor, variable, or uncertain outcomes. Farming under climate change is an uncertain business, as is farming in a politically unstable environment or for highly price-volatile food markets. Negative agricultural outcomes also result from pests and diseases, inadequate marketing infrastructure, financial constraints, insufficient support services, and socio-cultural dynamics. Farmers nearly always grapple with multiple simultaneous risks, some of which are of greater priority or impact than others. The type and degree of risks that comes with an intervention and farmers' degree of risk aversion often heavily influence farm choices [30]–[32].

Historically, peer-reviewed literature has identified five categories of agricultural risks [33]:

- **production** (manifested through yield reductions or instability due to weather, climate, pests, diseases, soil salinity, *etc*.);
- **market** (associated with uncertain prices, costs, and inadequate market access due to variable yields, energy prices, international trade, *etc*.);
- **institutional** (related to distortionary or unpredictable changes in policies, regulations, or informal institutions, such as trading negotiations);
- **financial** (associated with lack of credit or changing credit conditions, increasing or variable interest rates, *etc*.);
- **personal** (relate to the individual and can be manifested through injuries from using machinery, illness or death from diseases, including diseases transmitted from livestock).

Production risks are documented in 66% of studies; market risks are examined in 13%, and the remaining the categories each appear in 2% of the relevant literature. About 15% of studies analyzed two or more types of risk. The preponderance of production risk analyses is unsurprising. Production risks are almost always ranked as most important by smallholder farmers [33], [34]. Importantly, it is also the one they can address directly, whether through informal strategies such as income diversification, management practices, *etc*., or through formal strategies such as subsidies, insurance, and credit. Compared to other types of risks (such as institutional, personal, financial), production risks are also relatively more straightforward to quantify and obtain data for (See section on Data sources).

Production risks are more broadly underpinned by factors outside the farmers' control, including climate hazards (e.g. droughts and heat waves), biological factors (*e.g.*, pests and diseases), financial constraints (*e.g.*, a lack of credit services, and market limitations (*e.g.*, lack of improved seed). Whilst the mean performance of an "improved" practice or technology vs a control may be positive for an outcome, it is important to consider how variable this outcome is. Farmers may have minimum acceptable thresholds for seasonal yields that relate to their short-term household needs; if an improved practice is more productive on average, but this is associated with increased variability, the chance of not meeting a minimum threshold for any given year could increase (compared to business as usual). This may be unacceptable for the potential adopter. Time-series yield data allows to empirically explore how risky adopting a practice or technology is. Table 2 details two methods that can be used to explore production risks: 1) lower confidence limit (LCL) and 2) Relative Yield Stability Ratio (CVR).

Table 2. Examples of proxies for production risks [35]-[38]

Indicator	Definition	Calculation/ Formula	Interpretation/ Use
Lower confidence limit (LCL)	• Probability that the technology will give a yield below the minimum acceptable yield. Calculated over a period of at least three years.	Risk (confidence interval) = $(mean - (t_{d.f.} = n - 1, p)\ (\sigma)/n^{1/2}$ where: n = number of observations used to calculate the mean of the group; t= values from a one-tailed t-table; $d.f.$ = the degrees of freedom associated with the mean; σ = standard deviation associated with the mean; p = the chosen probability level in one-tailed t-table (0.5 in this case).	• The lower the LCL value the higher the risk a technology yields below business as usual. • A low LCL value indicates the technology is risky and may not offer farmers the expected returns
Relative Yield Stability Ratio (CVR)	• Based on the coefficient of variation (CV: standard deviation across years divided by the mean across those years) of both treatments as indicator for variability. • Variability is standardized per unit yield (i.e., the variability relative to the yield level). • In order to account for the sampling uncertainty in each observation one can use the sampling variances [35].	$CVR = ln\left(\frac{CV_t}{CV_c}\right)$ with $CV_t = \left(\frac{SD_t}{X_t}\right)$ and $CV_c = \left(\frac{SD_c}{X_C}\right)$ where: SD = standard deviation; X_t = yield of experimental treatment; X_c = yield of control treatment.	• A ratio of greater than one indicates greater yield variability for the experimental treatment. • High variability has negative implications on liquidity, marketing, livelihoods, thus increasing risk.

Where there appear to be overall production benefits for an improve practice, but they appear variable in time or space we can assess if climate is likely to be the driver. Climate hazards can be specified for individual crops via the scientific literature and/or through direct engagement with stakeholders; for example, a farmer might define a hazard as a hot dry spell of more than 10 days after maize seeds germinate. Geo-spatial climate resources such as CHIRPS, CHIRTS, POWER, TERRACLIM or AFRICLIM can then be used to assess if a hazard occurred for a particular season to model the relationship of historical outcomes vs climate hazards. Such data could be used to extrapolate practice adoption risk across climate hazard maps to show the present risk and how this may change given climate change scenarios. Alternatively, crop modelling (e.g., DSSAT and APSIM) or niche modelling using machine learning methods can estimate how climate hazards (and climate change) will affect crop production (e.g., quantity, quality[7], and stability of yields across time).

Barriers

Agricultural risk management in general and CSA adoption in particular is conditioned by the wider context of human and social development, defined by variables such as education or degree of access to technology, markets, information, and finance, among others. Where broader societal conditions are underdeveloped or nonexistent (*i.e*., farmers access to technology is low or there is poor market information available), investment in CSA become less attractive (if not impossible) to smallholder farmers. Therefore, a discussion on the business case for CSA is not only about the extent to which CSA helps address different types of risks and achieve positive outcomes, but also about how “adoptable” the CSA investment is, from a (smallholder) farmer perspective. Barriers are drivers of risk (See Table 3); failure to identify and eliminate barriers can lead to the failure of the investment. Technology adoption studies and models can add valuable context to business cases, particularly where they address farmers’ cultural preferences.

There are many ways to categorize barriers. Much of the literature focusing on CSA uptake has placed great emphasis on economic barriers [39]. These are tightly linked to the economic performance of the practices/technologies and farmers’ short-term priorities and include, among others: high costs (during initial stages and/or implementation of practice), transaction costs (*e.g.,* monetary/non-monetary costs for negotiating prices with a trader), long pay-back periods, uncertain returns, high costs to benefit ratio, etc. Other types of adoption factors discussed in the literature include [14], [40]–[43]:

- **household characteristics** (*e.g.,* gender, age, household size, education, farming experience, access to credit/subsidies/safety nets),
- **farm characteristics** (*e.g.,* farm size, cropland area, number of livestock, etc.),
- **knowledge and information** (market and price information, availability of climate information services, capacity to interpret and use information, access to radio, mobile phone ownership, etc.),
- **institutions** (*e.g.,* policies and incentives favorable for smallholder production and **commercialization**, inter-sectoral coordination, trust in institutions, etc.)
- markets (*e.g.,* distance to markets, road network, etc.)
- **social and cultural norms** (*e.g.,* demand for certain farm products).

[7] Quality risk is particularly relevant where price is directly informed by quality; this is frequently the case for international commodities such as cacao and cashew.

The type of barriers and their magnitude vary across farmer contexts and investment type (specific practice/technology) and investment charactersitics (e.g., whether it's capital-, knowledge-, or labor-intensive). Most often, farmers' adoption of a CSA practice is hampered by multiple obstacles (e.g., knowledge and information, lack of access to productive resources, no ownership of land, etc.) and only lifting one or some of these barriers may not effectively solve the problem.

Table 3. How risks and barriers match in the context of climate-smart agriculture

Risk type	Barrier category	Barrier (Risk driver), expressed as limited/lack of
Production risks (Arising from adoption of new practices in a context of uncertainty, from limited farm input quality and availability or social/cultural norms)	Economic	▪ Visible immediate gains; ▪ Capacity to cover high initial/implementation/transaction costs; Delayed/uncertain returns
	Farm characteristics	▪ Farm size; ▪ Land tenure regime (discouraging long-term investments); ▪ Asset ownership (livestock, tractors, etc.); ▪ Farm input quality/availability (improved seed, fertilizer, etc.)
	Household (HH) characteristics	▪ Farming experience ▪ Savings/ safety nets to experiment with new practices/ technologies
	Knowledge & info	▪ Agricultural extension; ▪ Awareness of climate change impacts and/or of CSA options; ▪ Capacity to interpret and use climate and weather information on farm; ▪ Reliable information on market demand; ▪ Access to/ ownership of Information and communication technology (ICT) (radio, mobile phone)
	Markets	▪ Physical access to markets (paved roads, distance to markets);
	Social and cultural norms	▪ Consumer's reluctance to new farm products (new product types and varieties, processed products, etc.).
Financial risks (linked to lack of capital/ familiarity with financing options)	HH characteristics	▪ Adequate collateral of farmers or credit history for loans;
	Institutions	▪ Availability of local financial sector (e.g., local banks); ▪ Financial products tailored to smallholder's needs; ▪ Transaction costs for small loans for remote smallholder farmers
	Knowledge & info	▪ Risk assessment knowledge and capacity;
Market risks (Arising from limitations and uncertainty in access, prices)	Economic	▪ Transaction costs for smallholders in remote areas; ▪ Affordable finance to meet high up-front costs in marketing; ▪ Proven business models that demonstrate future pay-off;
	Institutions	▪ Organizational structures to enable bargaining power for farmers;
	Knowledge & info	▪ Awareness of climate change opportunities and risks; ▪ Access to radio; ▪ Mobile phone ownership;
	Markets	▪ Logistical infrastructure to diminish post-harvest loss and ensure sales; ▪ Road infrastructure (or distance to market in km)
Institutional risks (Arising from existing regulations and policies to support CSA)	Institutions	▪ Adequate climate change policies and strategies; ▪ Capacity to identify barriers to CSA and to design policies to lift the barriers; ▪ Budget to design and to implement policies for CSA; ▪ Cross-sectoral coordination to promote integrated policies; ▪ Licensing policies and processes for use of new technologies; ▪ Perverse incentives that promote unsustainable practices (e.g., fossil fuel subsidies) ▪ Political instability and corruption ▪ Trust in institutions (especially on economic actors' side)
Personal risks (specific to the individual)	Farm characteristics	▪ Labor availability during key agricultural periods; ▪ Health condition of household members;
	HH characteristics	▪ Literacy;

Source: Adapted by authors, based on literature [44].

Data sources

A business case for CSA typically begins with a standard farm budget, or enterprise budget (EB). An EB includes estimates of income (returns), costs (variable, fixed, and total), and profits (*e.g.*, net returns) associated with a farm investment over a specific time period, ideally multiple years. While EBs are standard in developed economies, tropical smallholder operations that maintain EBs are the exception, not the rule.

An EB can be constructed using available literature (see case studies below). Analyzing existing datasets to provide new insights can significantly reduce research costs and maximize the benefits of previous data collection efforts. Nevertheless, some countries and development contexts are better studied than others [45]. Additionally, many potentially promising technologies remain significantly underexplored (such as post-harvest technologies), and some outcomes are rarely analyzed and reported (*such as* socio-cultural outcomes and institutional risks). The structure of farm budgets varies widely, and studies report economic data inconsistently.

Collecting EB primary data is substantially more time- and cost-intensive than leveraging existing data. However, it also facilitates greater control over the populations and samples selected (*e.g.*, the most vulnerable farmers in a dry area), the types of data collected, the methods used to measure variables, *etc*. In many settings, multi-disciplinary and cross-sectoral collaboration will be crucial to obtaining robust data and insights into the multiple facets of farm profitability and risks.

Several opportunities also exist for constructing EBs as part of a larger development program, targeting financial literacy for individual farmers, farmer groups, and cooperatives. Concepts such as accurate recordkeeping, transparency, budgeting, investment, savings, and bank services are critical for any small business or organization. One example for building farm literacy is the "leaky bucket" model used in asset-based community development approaches [46]. In many countries, digital solutions can support and enable financial literacy learning, good financial practices, and access to financial services[8].

Various tools and extension materials support financial literacy and EB development. FAO's booklet series aimed at agricultural field workers in farmer trainings provide step-by-step guides of establishing cash flow and savings, explain profitability, financial record keeping, how to

[8] See Ghana-based apps like Farmerline or AgroCenta or Kenya-based OrganiCredit that enable digital farm record keeping.

manage risks and how to use financial instruments [47]. The Michigan State's Crop Budget Estimator [48] requires access to Microsoft Excel and facilitates farm management decisions. Other examples include the Penn State Extension EB templates [49], or the AgriSETA guide to farm budgets and practical farm information systems [50]. The Handbook on Agricultural Production Costs Statistics provides detailed guidelines on collecting, compiling and reporting farm data, including information on survey costs [51].

Once an EB is established, risk data is used to build out the business case. Quantitative and qualitative farmer surveys and field experiments will provide the bulk of the necessary production and personal risk data, including farmers' attitudes, responses, and preventative strategies. Market risks are largely quantified using agricultural price data, while financial and institutional risk identification and quantification requires an understanding of the banking/financial environment and the policy/regulatory context. Context-specific insights into barriers to CSA uptake are preferably collected through farm surveys or qualitative interviews but where resources lack and the scope of the assessment is broader, the business case can draw on the literature available on agricultural technology uptake.

Case studies: Applying the framework in Kenya and Malawi

Data

The business case reports for Kenya and Malawi were developed as part of a collaboration between the United States Department of Agriculture-Foreign Agriculture Service (USDA-FAS) and World Agroforestry (ICRAF) to present to decision makers in Kenya and Malawi. The two briefs distill critical information on the benefits, costs, and risks associated with different agricultural management options common to the maize-mixed systems in the two countries from a smallholder farmer's perspective.[9] The reports are available on CG Space (Kenya: https://hdl.handle.net/10568/109031 Malawi: https://hdl.handle.net/10568/109030).

Four themes underpin the business cases, each reflecting key considerations for investment planning, prioritization, and management:

- **Context:** sets the scope of the business case, highlighting key facts regarding the application domain for each practice/technology, such as agro-environmental, climate and food security conditions, among others.

[9] Maize is the national dietary staple and predominates smallholder farming systems in both countries. Production across both countries is stifled by low or declining soil fertility, land degradation, unreliable rainfall, pests and diseases, and low adoption rates of CSA practices that could improve resilience in the face of these challenges.

- **Economic performance**: highlights costs and returns of agricultural technologies to help investors anticipate eventual economic gains and losses from the CSA investment(s).
- **Risks**: reveals the degree of riskiness of the CSA investment, considering production factors that may affect investor's' interest in adopting and maintaining the technology over time
- **Barriers**: flags potential caveats and highlights additional investments required to create favorable conditions for adoption, maintenance and scaling of the technology.

While the list of themes and related indicators is by no means exhaustive, particularly given the narrow scope of the business cases, it provides users with entry-points for holistically understanding the investment viability and effectively allocating resources. The scope included only the agricultural technologies considered relevant for addressing key maize-based system challenges in Kenya and Malawi: agroforestry, soil, crop, or nutrient management practices implemented at farm- or field-level.

Economic performance, risks, and barriers data were extracted from peer-reviewed studies included in the ERA database (Box 1). The selected studies (27 from Kenya and 7 form Malawi[10]) were published between 1970 and 2013 and reported primary data from farms, fields, and households, and included both a control (BAU, conventional farm practice, or baseline) and CSA practice treatment [52]. Data extracted from ERA included study variables (study code, author, publication year), practice variables (theme, practice name, production system, control and treatment descriptions, varieties used), and outcomes (means, control and treatment results, and percent change). All monetary values were converted to 2010 US$.

Risk data included crop yields and minimum and average acceptable values according to smallholder farmers. Risks were expressed in terms of potential for yields below the mean control (0.5). Risk was calculated for a unique practice[11] within a site[12]. For CVR, data from multiple studies were combined [35]. For LCL risk, the same method as above was not feasible. Instead, when combining data, we took the weighted mean of all the LCL values for a practice in ERA. An observation was weighted as:

$$\left(\frac{Replicates^2}{2*Replicates}\right)/N.Obs.Study$$

[10] For a full list, see https://era.ccafs.cgiar.org/query/app/.
[11] A unique practice has everything held the same other than the experimental practice (with some pragmatic exceptions, *e.g.* in no-till papers it is acceptable to substitute physical for chemical weeding).
[12] A site is the spatial unit of reporting within a publication and can be very precise, e.g. a field, or more diffuse, e.g. where results are aggregated from several villages with a region.

Basically, an observation was upweighted if it came from a study with lots of replication and downweighted according to the number of other observations contributed by the same study for that practice (e.g., different levels of fertilizer application or different types of manure added).

The economic indicators VC, GM, and GR were identified as most relevant for the scope of this business case given the availability of data. NPV, BCR and PP, although highly valuable, were rarely and inconsistently reported, and were thus excluded from these business cases. Reward was calculated as the ratio between VC and GR. Barriers data was primarily qualitative, and thus were presented as narratives.

Data from ERA were aggregated at both the study (across years and observations) and dataset (across studies) levels to enable multi-scale analyses. Hence, the business cases represent the average performance of the technologies from multiple studies over multiple timeframes and agroecological zones. Aggregation carries the risk of obscuring details and introducing subjectivity bias [53], but also allows for the synthesis of large volumes of data into practical messages for diverse consumers.

Box 1 Evidence for Resilient Agriculture (ERA) database: criteria for data extraction and data quality assurance

In ERA data are screened and extracted according to the following criteria:

- There must be a practice vs a control;
- They must have a location;
- These should be co-located as reasonable given the spatial scale at which a practice or technology is applied;
- Data must be from a peer-reviewed publication. Even so, data is still checked for errors during in extraction and authors contacted in case of unusual outcomes;
- Only primary data is collected (no modelled outcomes are included in ERA);
- Practice and outcome definitions much match the ERA concept scheme. Classification is first based on practices or outcome descriptions (rather than only on author naming), so as to avoid issues with inconsistent use of terminology;
- Extreme outliers >3 interquartile range distance from the mean are excluded from the data.
- Data should come from a realistic setting (data extrapolated from laboratory or plot-trials are not accepted);

During data extraction a range of validation methods are employed to minimize the chance of transcription errors. Data from a publication are quality controlled at least once and by someone different to the person who performed the extraction. After extraction further validation logic is automated in R to search for potential errors. These are then screened and corrected, as necessary. As such fidelity to the original data is very high and the quality of these data as good as can be obtained for the context.

Findings

Detailed findings can be identified in the business case reports. Here, we distill key insights, in order to showcase the value of the information delivered by such succinct analyses. Table 4 presents sample on economic performance of different farm management practices in Malawi. On average, soil management technologies perform among the best of all major practice categories included in the analysis, as a result of relatively small increases in VCs (otherwise required for herbicide, sprayers and gear for weed control) compared to farmers' practice and of significant growth in gross returns. Relatively low increased costs combined with high relative returns generates the ability for farmers to generate gross margins of up to 50% more than business as usual (BAU).

Table 4 Average economic performance of selected agricultural technologies for maize in Malawi. Values for "Improved practice" are expressed in USD/ha (2010 US$). "Percent change" refers to change from farmer (conventional) practice. Yellow color suggests negative outcomes (losses), greens suggests positive outcomes (light green increases up to 50%, dark green more than 50%).

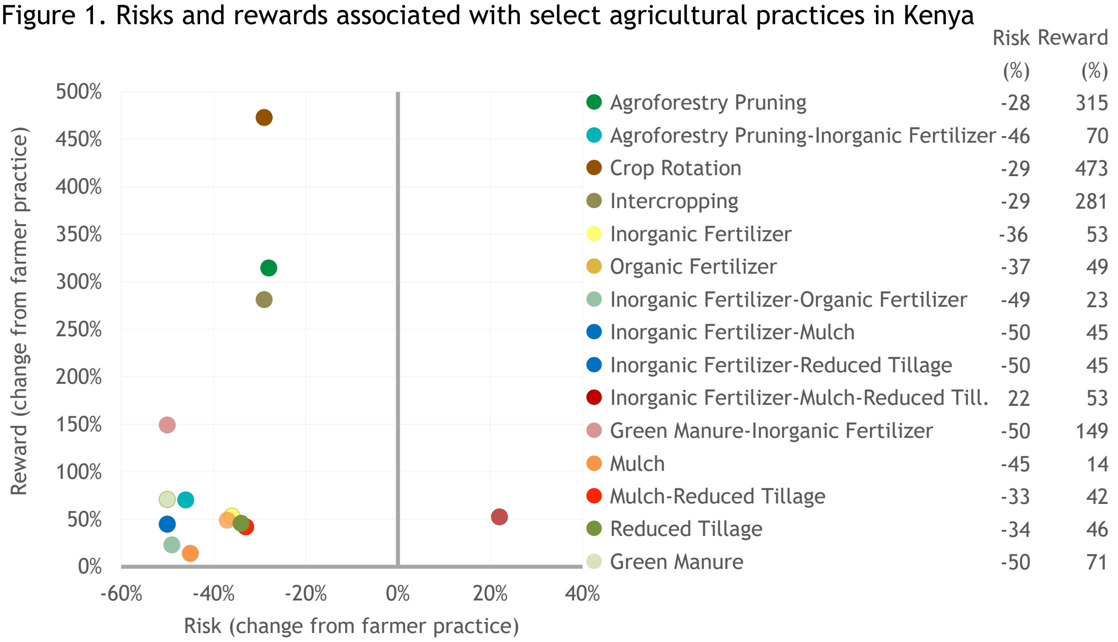
	VARIABLE COSTS		GROSS RETURNS		GROSS MARGINS	
	Improved practice	Percent change	Improved practice	Percent change	Improved practice	Percent change
AGROFORESTRY (ALL)	72	37%	450	1%	377	-3%
Alleycropping (Tephrosia vogelii + Improved Maize Variety)	72	37%	450	1%	377	-3%
SOIL MANAGEMENT (ALL)	372	19%	1235	29%	634	47%
Intercropping (Maize/Bean)	318	15%	2499	13%	281	53%
Intercropping + Mulch (Maize-Cowpea; Maize-Pigeon pea)	509	10%	1217	3%	710	-1%
Crop Rotations (Maize/Groundnut; Maize/Groundnut/Pigeon pea)	100	84%	731	63%	631	38%
Mulch + Intercropping + Green Manure (Maize-Pigeon pea)	364	-12%	956	-1%	698	27%
Reduced Tillage + Mulch	439	6%	1069	39%	659	54%
Reduced Tillage + Mulch + Intercropping (Cowpea, Pigeon pea)	509	23%	1217	46%	762	57%
Reduced Tillage + Mulch + Intercropping + Green Manure	364	7%	956	40%	698	105%
NUTRIENT MANAGEMENT (ALL)	62	55%	472	49%	300	61%
Green Manure (Maize/Mucuna; Maize/Groundnut/Pigeon pea)	74	36%	490	-5%	416	-9%
Inorganic Fertilizer	35	35%	239	60%	274	56%
Inorganic Fertilizer + Intercropping (Maize-Bean)	35	No data	124	142%	159	210%
Inorganic Fertilizer + Improved Maize Varieties	105	94%	454	-1%	349	-14%

Figure 1 reports data on risks and rewards associated with different farm management practices in Kenya. Risk analysis considered crop yields and minimum and average acceptable values for smallholder farmers. Risks are expressed as the possibility of yielding lower than the mean control value (0.5). Negative values indicate a lower risk to farmers compared to BAU. Rewards are expressed as BCR. Positive BCR indicates economic benefits for farmers.

Accordingly, agroforestry prunings and crop diversification options (intercropping, crop rotations) bring high rewards (higher benefits compared to costs) and have the potential to reduce production risks by up to 29%. However, the benefits and costs vary greatly with types of crops, trees, management practice and agro-climatic conditions, details that this figure does not capture. In areas with poor soils and inadequate replenishment of plant nutrients, the combination of crops, trees and mineral fertilizer has more potential to decrease maize production risks compared to sole maize planting or maize fertilized with tree prunings; however, rewards are not as attractive, due to the high price of fertilizer and tree seeds.

Figure 1 also highlights that nutrient management practices produce mixed results, with maize under a combination of reduced tillage, mulch and inorganic fertilizer, being riskier compared to maize under conventional tillage practices and no fertilizer, but still viable from an economic point of view. Such trade-offs between production/food security and income/resilience outcomes are not exceptional, but characteristic to farm landscapes. Generating and sharing knowledge about the performance of management options can help farmers take more informed, context-tailored decisions.

Figure 1. Risks and rewards associated with select agricultural practices in Kenya



The business cases reports support investors in anticipating the profitability, risks, opportunities, and barriers of diverse farm operations. They further illustrate the potential value of existing datasets to uncover new insights into agricultural investment feasibility from a smallholder farmer perspective. Nevertheless, caution is warranted when interpreting and applying business case results. The performance values presented in the two case studies do not provide definitive, unifying, or globally relevant conclusions. Rather, they demonstrate what farmers and investors could expect, on average, from an intervention under comparable conditions. In reality, farmers may not strictly follow a best practice, and most farmers do not implement and monitor practices as meticulously as researchers conducting controlled experiments do [54]. Even in controlled experiments, there is significant variation between and within studies. Hence, business cases are best considered initial insights into which opportunities warrant additional consideration in a particular setting.

Conclusion and recommendations

More than ten years of research and practice suggest that CSA is a viable approach to transforming the agricultural sector. Ultimately, the adoption of CSA practices sits with the private sector, and particularly farmers. Insight into the economic performance, risks, and barriers of these practices is necessary in order to demonstrate their utility in meeting the goals of enterprise. To date, existing datasets have been primarily used to advocate for solutions-oriented research, development programs, and, to a lesser extent, policy. There remains tremendous opportunity to expand the utility of existing data to establish business cases for CSA interventions. Business cases can be tailored to the user and broadly applied to everything from mixed crop-livestock systems to energy management. This working paper puts forth a general framework for assessing the business case for CSA from a smallholder farmer's perspective. The protocol can be tailored to the unique business needs of any given situation and should be seen as an initial insight into which opportunities warrant further attention.

References

[1] P. Smith *et al.*, “Policy and technological constraints to implementation of greenhouse gas mitigation options in agriculture,” *Agric. Ecosyst. Environ.*, vol. 118, no. 1–4, pp. 6–28, Jan. 2007.

[2] S. J. Vermeulen, B. M. Campbell, and J. S. I. Ingram, “Climate Change and Food Systems,” *Annu. Rev. Environ. Resour.*, vol. 37, no. 1, pp. 195–222, Oct. 2012.

[3] J. F. Morton, “The impact of climate change on smallholder and subsistence agriculture,” *Proceedings of the National Academy of Sciences of the United States of America*, vol. 104, no. 50. National Academy of Sciences, pp. 19680–19685, 11-Dec-2007.

[4] V. Ricciardi, N. Ramankutty, Z. Mehrabi, L. Jarvis, and B. Chookolingo, “How much of the world’s food do smallholders produce?,” *Glob. Food Sec.*, vol. 17, no. January, pp. 64–72, 2018.

[5] D. B. Lobell, W. Schlenker, and J. Costa-Roberts, “Climate trends and global crop production since 1980,” *Science (80-.).*, vol. 333, no. 6042, pp. 616–620, Jul. 2011.

[6] U. Adhikari, A. P. Nejadhashemi, and S. A. Woznicki, “Climate change and eastern Africa: a review of impact on major crops,” *Food Energy Secur.*, vol. 4, no. 2, pp. 110–132, Jul. 2015.

[7] B. M. Campbell, P. Thornton, R. Zougmoré, P. van Asten, and L. Lipper, “Sustainable intensification: What is its role in climate smart agriculture?,” *Curr. Opin. Environ. Sustain.*, vol. 8, pp. 39–43, 2014.

[8] A. Jarvis *et al.*, “An Integrated Adaptation and Mitigation Framework for Developing Agricultural Research: Synergies and Trade-Offs,” *Exp. Agric.*, vol. 47, no. 2, pp. 185–203, 2011.

[9] J. A. Foley *et al.*, “Solutions for a cultivated planet,” *Nature*, vol. 478, no. 7369, pp. 337–342, Oct. 2011.

[10] FAO, *Climate-Smart Agriculture Sourcebook*, 2nd Editio. Rome: Food and Agriculture Organization (FAO), 2017.

[11] P. Bell *et al.*, “A Practical Guide to Climate-Smart Agriculture Technologies in Africa,” Wageningen, The Netherlands, 224, 2018.

[12] T. S. Rosenstock, A. Nowak, and E. Girvetz, *The Climate-Smart Agriculture Papers*. Springer, 2019.

[13] L. Lipper *et al.*, “Climate-smart agriculture for food security,” *Nat. Clim. Chang.*, vol. 4, no. 12, pp. 1068–1072, 2014.

[14] A. A. Kimaro *et al.*, “Is conservation agriculture ‘climate-smart’ for maize farmers in the highlands of Tanzania?,” *Nutr. Cycl. Agroecosystems*, vol. 105, no. 3, pp. 217–228, Jul. 2016.

[15] E. Bryan, C. Ringler, B. Okoba, J. Koo, M. Herrero, and S. Silvestri, “Can agriculture support climate change adaptation, greenhouse gas mitigation and rural livelihoods? insights from Kenya,” *Clim. Change*, vol. 118, no. 2, pp. 151–165, Dec. 2013.

[16] J. Barnard, H. Manyire, E. Tambi, and S. Bangali, *Barriers to scaling up / out climate smart agriculture and strategies to enhance adoption in Africa*. 2012, p. 10.

[17] K. L. Steenwerth *et al.*, “Climate-smart agriculture global research agenda: scientific basis for action,” *Agric. Food Secur.*, vol. 3, no. 1, p. 11, 2014.

[18] C. Thierfelder, W. Bunderson, and W. Mupangwa, “Evidence and Lessons

Learned from Long-Term On-Farm Research on Conservation Agriculture Systems in Communities in Malawi and Zimbabwe," *Environments*, vol. 2, no. 4, pp. 317–337, Jun. 2015.
[19] F. K. Akinnifesi *et al.*, "On-Farm Assessment of Legume Fallows and Other Soil Fertility Management Options Used by Smallholder Farmers in Southern Malawi," *Agric. J.*, vol. 4, no. 6, pp. 260–271, 2009.
[20] M. Mutamba and O. Ajayi, "A Business Case for Engaging the Private Sector in Climate-smart Solutions for Smallholder Farmers," Wageningen, The Netherlands, 2018.
[21] U. M. Gordon, T. Were, and O. Ajayi, "Putting the private sector at the centre of climate-smart agriculture," Wageningen, The Netherlands, 2019.
[22] C. R. Canavan, L. Graybill, W. Fawzi, and J. Kinabo, "The SDGs Will Require Integrated Agriculture, Nutrition, and Health at the Community Level.," *Food Nutr. Bull.*, vol. 37, no. 1, pp. 112–5, Mar. 2016.
[23] R. O. Zerbe and A. S. Bellas, "A primer for understanding benefit-cost analysis," 2015.
[24] Gittinger J. Price, *Economic analysis of agricultural projects*, Second Edition. World Bank, 1982.
[25] Robert J. Brent, *Applied Cost-benefit Analysis*, Second Edition. Cheltenham, UK: Edward Elgar Publishing Limited, 2006.
[26] G. Sain *et al.*, "Costs and benefits of climate-smart agriculture: The case of the Dry Corridor in Guatemala," *Agric. Syst.*, vol. 151, pp. 163–173, 2017.
[27] S. K. Ng'ang'a *et al.*, "Cost and benefit analysis for climate-smart agricultural (csa) practices in the coastal savannah agro-ecological zone (AEZ) of Ghana," Cali, 2017.
[28] A. S. Chaudhury, A. Helfgott, T. F. Thornton, and C. Sova, "Participatory adaptation planning and costing. Applications in agricultural adaptation in western Kenya," *Mitig. Adapt. Strateg. Glob. Chang.*, vol. 21, no. 3, pp. 301–322, Mar. 2016.
[29] P. Weston and R. Hong, "Social Return on Investment Report. Talensi Farmer-Managed Natural Regeneration Project in Ghana," Victoria, Australia, 2013.
[30] M. Marra, D. J. Pannell, and A. Abadi Ghadim, "The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve?," *Agric. Syst.*, vol. 75, no. 2–3, pp. 215–234, Feb. 2003.
[31] S. A. Javed, A. Haider, and M. Nawaz, "How agricultural practices managing market risk get attributed to climate change? Quasi-experiment evidence," *J. Rural Stud.*, vol. 73, pp. 46–55, Jan. 2020.
[32] J. B. Hardaker, "Some Issues in Dealing with Risk in Agriculture," 2000.
[33] A. M. Komarek, A. De Pinto, and V. H. Smith, "A review of types of risks in agriculture: What we know and what we need to know," *Agric. Syst.*, vol. 178, pp. 1–10, Feb. 2020.
[34] J. R. Anderson and J. L. Dillon, *Risk Analysis in Dryland Farming Systems*. Rome: Food and Agriculture Organization of the United Nations, 1992.
[35] S. Knapp and M. G. A. van der Heijden, "A global meta-analysis of yield stability in organic and conservation agriculture," *Nat. Commun.*, vol. 9, no. 1, pp. 1–9, Dec. 2018.
[36] D. Sirrine, C. Shennan, S. Snapp, G. Kanyama-Phiri, B. Kamanga, and J. R. Sirrine, "Improving recommendations resulting from on-farm research: Agroforestry, risk, profitability and vulnerability in southern Malawi," *Int. J.*

Agric. Sustain., vol. 8, no. 4, pp. 290–304, 2010.
[37] C. Müller *et al.*, “Global patterns of crop yield stability under additional nutrient and water inputs,” *PLoS One*, vol. 13, no. 6, p. e0198748, Jun. 2018.
[38] B. C. G. Kamanga, S. R. Waddington, M. J. Robertson, and K. E. Giller, “Risk analysis of maize-legume crop combinations with smallholder farmers varying in resource endowment in central Malawi,” *Exp. Agric.*, vol. 46, no. 1, pp. 1–21, 2010.
[39] G. Fusco, M. Melgiovanni, D. Porrini, and T. M. Ricciardo, “How to improve the diffusion of climate-smart agriculture: What the literature tells us,” *Sustain.*, vol. 12, no. 12, pp. 1–16, 2020.
[40] R. A. B. Kpadonou, T. Owiyo, B. Barbier, F. Denton, F. Rutabingwa, and A. Kiema, “Advancing climate-smart-agriculture in developing drylands: Joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel,” *Land use policy*, vol. 61, pp. 196–207, Feb. 2017.
[41] M. Ouédraogo, P. Houessionon, R. B. Zougmoré, and S. T. Partey, “Uptake of Climate-Smart Agricultural Technologies and Practices: Actual and Potential Adoption Rates in the Climate-Smart Village Site of Mali,” *Sustainability*, vol. 11, no. 17, pp. 1–19, 2019.
[42] B. K. Kurgat, C. Lamanna, A. Kimaro, N. Namoi, L. Manda, and T. S. Rosenstock, “Adoption of Climate-Smart Agriculture Technologies in Tanzania,” *Front. Sustain. Food Syst.*, vol. 4, no. 3, p. 55, May 2020.
[43] N. McCarthy, L. Lipper, and D. Zilberman, “Economics of climate smart agriculture: An overview,” in *Natural Resource Management and Policy*, vol. 52, Springer, 2018, pp. 31–47.
[44] Y. Glemarec, “Addressing the gender differentiated investment risks to climate-smart agriculture,” *AIMS Agric. Food*, vol. 2, no. 1, pp. 56–74, 2017.
[45] T. J. Krupnik, J. A. Andersson, L. Rusinamhodzi, M. Corbeels, C. Shennan, and B. Gérard, “Does size matter? a critical review of meta-analysis in agronomy,” *Exp. Agric.*, vol. 55, no. 2, pp. 200–229, Oct. 2019.
[46] B. Peters, M. Gonsamo, and S. Molla, “Capturing unpredictable and intangible Change: evaluating an Asset-based Community development (AbCD) Approach in Ethiopia,” 10, 2011.
[47] FAO, “Financial education for farmers,” 2012.
[48] J. Laporte, “Crop Budget Estimator Tool This factsheet helps to explain the key concepts and uses of the Crop Budget Estimator Tool.”
[49] PennState Extension, “Budgeting for Agricultural Decision Making,” Pennssylvania, 2019.
[50] AgriSETA, “A farm budget and a proper information system.”
[51] FAO, “Agricultural Cost of Production Statistics. Guidelines for Data Collection, Compilation and Dissemination Publication prepared in the framework of the Global Strategy to improve Agricultural and Rural Statistics,” Rome, 2016.
[52] T. S. Rosenstock *et al.*, “The scientific basis of climate-smart agriculture A systematic review protocol,” 2016.
[53] A. L. Mayer, “Strengths and weaknesses of common sustainability indices for multidimensional systems,” 2007.
[54] T. J. Krupnik, J. A. Andersson, L. Rusinamhodzi, M. Corbeels, C. Shennan, and B. Gérard, “Does size matter? a critical review of meta-analysis in agronomy,” *Exp. Agric.*, vol. 55, no. 2, pp. 200–229, 2019.

[55] FAO, “Agro-Ecological Zoning Guidelines. FAO Soils Bulletin 76 ,” Rome, 1996.

CGIAR

RESEARCH PROGRAM ON
Climate Change, Agriculture and Food Security

CCAFS

The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) brings together some of the world's best researchers in agricultural science, development research, climate science and Earth system science, to identify and address the most important interactions, synergies and tradeoffs between climate change, agriculture and food security. For more information, visit us at **https://ccafs.cgiar.org/.**

Titles in this series aim to disseminate interim climate change, agriculture and food security research and practices and stimulate feedback from the scientific community.

CCAFS is led by:

Alliance

Bioversity International

CIAT International Center for Tropical Agriculture

CCAFS research is supported by:

CGIAR

Australian Government, Australian Centre for International Agricultural Research

Irish Aid, An Roinn Gnóthaí Eachtracha agus Trádála, Department of Foreign Affairs and Trade

Ministry of Foreign Affairs of the Netherlands

New Zealand Foreign Affairs & Trade Aid Programme

Schweizerische Eidgenossenschaft, Confédération suisse, Confederazione Svizzera, Confederaziun svizra, Swiss Agency for Development and Cooperation SDC

UKaid from the British people

European Union

USAID from the American people

IFAD Investing in rural people