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Modelling Farm-household Livelihoods in Developing Economies

Insights from three country case studies using LSMS-ISA data

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Foreword

The European Commission's Joint Research Centre (JRC) was requested by the Directorate-General for International Cooperation and Development (DG DEVCO) to provide DEVCO thematic units and the EU Delegations with independent, evidence-based scientific and technical support in the areas of agriculture and food and nutrition security (FNS) in sub-Saharan Africa (SSA)([1]).

Within this framework, the Economics of Agriculture Unit of the JRC is engaged in microeconomic analysis of agriculture and food security in SSA, particularly in developing impact analyses that are relevant to policy. This research activity consisted of developing a micro-simulation model for *ex ante* impact assessment of selected national agricultural policies and EU cooperation policies (e.g. European Development Fund programmes) on food security and rural poverty alleviation in SSA.

In this report we describe the rationale for this activity, as well as the design and main features of the microeconomic model FSSIM-Dev (Farming System Simulator for Developing Countries) used for this purpose. FSSIM-Dev is an optimization model that operates at the farm household level and is applied across a representative sample of the rural farm population. The capability of the model is illustrated in this report, along with a comprehensive analysis of selected policies aimed at boosting farm performance and ensuring food security in selected sub-Saharan African countries, namely Ethiopia, Niger and Tanzania.

([1]) This request was formalized in December 2013 under the Administrative Arrangement JRC No. 33272-2013-10 DEVCO 325-863 'Technical and scientific support to agriculture and food and nutrition security sectors' (TS4FNS).

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Abstract

This report presents the FSSIM-Dev (Farming System Simulator for Developing Countries) model, which is one of the decision-making tools developed by the JRC to provide independent evidence-based policy analysis in the areas of food and nutrition security and sustainable agriculture, specifically in sub-Saharan Africa. It aims to stimulate dialogue between scientists and policymakers, and to challenge them in better addressing the question of the ‘last mile’ between research results and concrete decision-making.

FSSIM-Dev is a farm household model used to *ex ante* assess the impacts of agri-food policies and technological innovations on food security and rural poverty alleviation, in the specific context of low-income/developing countries. It aims to inform policymakers on how changes in prices, technology, food and agricultural policies might affect the viability, poverty and food security of heterogeneous sets of farm households that characterize the agricultural sector, which types of farm households will be most affected, where these most-affected farms are located, etc.

The report provides a detailed description of the FSSIM-Dev model in terms of design, mathematical structure, data preparation, calibration process, and modelling of household (market) decisions. The rationale, theoretical background, technical specification and main indicators that can be generated from this model are also presented and discussed.

The report also presents a comprehensive summary of results from the application of FSSIM-Dev to three countries: Ethiopia, Niger and Tanzania. Data from the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS–ISA) ([2]), which provide a national representative survey of the rural population with a focus on the farming sector, were used in these three country case studies.

([2]) http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA

1 Introduction

Food and nutrition security has become one of the most important items on today's international political agenda, and a serious issue for governments around the world. Guaranteeing a sustainable and equitable food supply in the context of climate variability and climate change, price volatility, the global financial crisis and demographic growth is a challenging task. Even though food availability has grown significantly and consistently over time, both globally and in developing countries, access to food is still limited, particularly in many low-income economies. The latest available estimates indicate that about 795 million people in the world were undernourished in 2016, 780 million of whom were living in developing countries (FAO et al., 2015). Although poverty continues to decline in many countries, major progress is yet to be made in rural areas of sub-Saharan Africa (SSA) and South Asia, where a large proportion of the population is extremely poor (52% of the rural population in SSA and 27% of the rural population in South Asia) and undernourished (FAO et al., 2015). Approximately one person out of four in SSA is estimated to be undernourished today.

Despite the decline of around 30% in the prevalence of hunger in SSA between the base period (1990-92) and 2015, substantial differences persist across SSA sub-regions and individual countries. Progress has been particularly remarkable in West Africa, which has more than halved the proportion of its people suffering from hunger. Continued efforts are needed in Central Africa, where undernourishment increased by around 10% compared to the base period. There is thus an urgent need to improve food and nutrition security in SSA, particularly in the Central Africa sub-region.

Most of the poor in SSA (82% according to Beegle et al., 2016) still live in rural areas, earning the majority of their income from agriculture. Around 92% of rural households in SSA are involved in farming to some extent, and an average African rural household earns about three quarters of its income from agriculture (Davis et al., 2017).

Despite farmers in SAA being the most vulnerable and the most food insecure, they can be the engine for growth and poverty alleviation. Empirical evidence shows that agricultural growth in SSA can be 11 times as effective in reducing extreme poverty as growth in other sectors (FAO et al., 2012). According to FAO (2015), only countries that have managed to secure agricultural productivity gains have succeeded in reducing undernourishment. Other studies have also shown that agricultural growth is essential for poverty reduction, and leads to consumption and production linkages in the overall economy, particularly in countries where rural poverty accounts for the largest share of total poverty (Ravallion and Datt, 2002; Ravallion and Datt, 1996; Hazell and Haggblade, 1990).

Given the overwhelming evidence that agriculture is a key driver of poverty alleviation in SSA, national governments and their development partners have developed – and continue to develop – several policies and programmes aimed at removing or reducing the challenges faced by farms in boosting their economic growth. These challenges include: low levels of agricultural productivity; limited use of inputs (mainly fertilizer) and improved varieties; limited access to finance (credit and insurance) and capital; inadequate access to modern markets; food price volatility; rise of agriculture-related health risks and food insecurity conditions (FAO et al., 2015).

However, many SSA countries currently face difficulties in setting priorities, in terms of policies and actions for addressing these challenges, due to a lack of high-quality data and appropriate analytical tools. The increasing complexity of agriculture, its environment and consequently agricultural systems, have made decision-making regarding production, marketing, finance and policies much more challenging and difficult. In addition, most policy analysts focused on *ex post* assessment of policies or programmes already implemented, rather than directly supporting the decision-making process. While such studies are crucial, to evaluate the effectiveness of policies and to be able to adjust, prolong or replace them, policymakers also need to know the possible outcomes of their new policies prior to implementation. The *ex ante* impact analysis of policies allows us to simulate different policy options and to compare them in terms of the size and distribution of their impact, as well as in terms of budgetary consequences, and thus to make informed policy choices.

The *ex ante* impact analysis of policies has become an integral and systematic part of political decision-making processes in a number of middle- and high-income countries. It provides independent and transparent evidence-based support to policymakers, without replacing political decision-making. It also allows safe and relatively cheap experimentation, prevents or corrects market and government failures, and increases the credibility of decision-making processes in the eyes of donors and the public.

Science has widely contributed to better informing *ex ante* impact analysis of new policies, and the body of literature and models for such purposes is increasingly dealing with different aspects and scales. They range from highly aggregated equilibrium models, like GTAP (Hertel 1997), to partial equilibrium models such as AGLINK-COSIMO (OECD 2006), and single farm behavioural models like FARMIS (Offermann et al., 2005) or IFM-CAP (Louhichi et al., 2018). Each of these models has its strengths and weaknesses and suitability for specific policy questions. Salvatici et al. (2000) and Britz and Heckelei (2008) have discussed the advantages and disadvantages of these different modelling approaches with respect to different types of policies and questions of interest. For example, single behavioural models such as farm-level models are more suitable for microeconomic analysis, as they provide detailed insights on the impacts of policy changes. If policy analysis aims to assess the impacts of policy change on a specific commodity market, or on the whole agricultural sector, partial (sector) equilibrium models can be used successfully. However, if there is also a particular interest in system-wide effects and spillover effects between different sectors, then computable general equilibrium models are more appropriate.

Despite their increasing number, most of these models – mainly the microeconomic models – are developed for the specific context of high-income countries. Consequently, they cannot easily be adapted and reused for other applications and contexts, such as SSA agriculture. This report tries to help fill this gap by proposing the microeconomic modelling tool FSSIM-Dev (Farming System Simulator for Developing Countries) for use in the specific context of low-income developing countries, to *ex ante* assess the impacts of agri-food policies on food security and rural poverty alleviation. FSSIM-Dev simulates how a given scenario, for example a change in prices or a new agricultural policy, might affect a set of indicators. Depending on the areas of interest to policymakers and stakeholders, such indicators may include changes in land use, input use, crop and animal production, farm household consumption and income, household food security, government expenditure, farmer participation in a given programme, or environmental externalities such as soil erosion and greenhouse gas emissions.

As such, this modelling tool can provide a detailed answer to a wide range of policy questions. For instance, it can show which alternative policies are more effective in stimulating agricultural production; whether different farm types/sizes respond differently to a specific policy; how various agricultural policies may contribute to food security and rural poverty alleviation; and how the benefits are distributed across the rural population.

We start with a short explanation of the motivation behind the focus on microeconomic analysis, and the rationale for the use of a farm-household optimization model. The report then provides a detailed description of the FSSIM-Dev model in terms of design, mathematical structure, data preparation, calibration process and modelling household (market) decisions. The theoretical background, the technical specification and the outputs that can be generated from this model are also briefly presented and discussed. The capability of the model is illustrated in this study through an analysis of the effects of selected policies on food security and rural poverty alleviation in three sub-Saharan African countries: Ethiopia, Niger and Tanzania.

2 Rationale for the focus on *ex ante* policy analysis at micro-level

As explained above, the main aim of this project is to support the policymaking process through simulating the potential effects of selected relevant measures. In particular, it uses a microeconomic modelling tool specifically built for *ex ante* assessment, at micro-level, of alternative national agricultural policy measures in developing countries, and EU cooperation programmes on food security and poverty alleviation.

Most research on agriculture and food security in SSA focuses on *ex post* analysis of policies or support programmes that have already been implemented. While such studies are crucial, to evaluate the effectiveness of policies and to assess, adjust, prolong or replace them, policymakers also need to take decisions before outcomes are realized. An *ex ante* policy assessment tool allows us to simulate different scenarios, to compare alternative policies – in terms of the size and distribution of their impact as well as the budgetary consequences – and thus to make informed policy choices.

In general, while macro-level tools can simulate agricultural policies at the aggregate level, a micro-level approach is needed to address detailed effects at the level of the single economic agent. The major motivations for developing a micro-level modelling tool are that: (1) agricultural and development policies are increasingly farm-specific; and (2) farm responses to policies are highly heterogeneous.

Price interventions, or universal fertilizer subsidies, target the agricultural sector as a whole; however, more specifically targeted policies are becoming increasingly important. Recognizing that smallholders are not a homogeneous group, national policies and assistance programmes may need to develop strategies that differentiate between farmers who may be 'moving up' into more productive systems and those who may be 'moving out' of farming. The choice should depend on the type of constraints faced by smallholders. If the main constraints are access to markets, inputs, credit and technologies, then these can potentially be fixed to help farmers move up. For example, fertilizer vouchers, extension programmes, provision of seeds or improved market access initiatives may be targeted at a specific group of farmers. Yet where the main constraints are of a more structural nature, such as densely populated, agriculturally unfavourable and remote areas, different policies may be needed, and smallholders may even be encouraged to move out of farming. Such targeted policies can only be assessed through micro-level tools.

Furthermore, responses to a specific policy are highly heterogeneous across farms. The impact of a single policy may be very different, depending on the farm location, resource endowment, land use, access to markets, land tenure, and the age, sex, economic status and composition of family members. This could particularly apply, for example, when dealing with policy instruments that trigger changes in production, consumption and labour supply. The magnitude and direction of these effects will depend on the behaviour of each agent, which differs depending on his/her characteristics, endowments, preferences and location. To capture heterogeneity across farms, and identify winners and losers under existing or alternative policies, micro-level analysis is therefore required.

We thus require a powerful micro-level modelling tool for *ex ante* analysis of the distributional impacts of specific agricultural and food security policies.

Our microeconomic tool focuses on modelling individual farm households. The prime decision-making unit in African agriculture is the farm household. It is also the unit where agro-economic innovations start, and where agricultural and agri-environmental policies trigger changes in land use, production and environmental externalities. In a farm household system, the household is managing the farm, is providing the main resources (land and labour) and is the major beneficiary of its production, either for own consumption or for the generation of cash income.

The main rationales for focusing on farm household systems are the following.

— The strong dominance of farm household–based agriculture in Africa, and the crucial role attributed to smallholders for enhancing agricultural productivity. 97% of farms in Africa are family farms (Graeub et al., 2016), and the great majority of these operate only small areas of land. About 80% of farms in SSA are considered smallholders, i.e. they cultivate an area smaller than 2 ha, and 95% of African farms are smaller than 5 ha (Lowder et al., 2016). Smallholders cultivate around 62% of the cultivated land, and provide up to 80% of the food supply (FAO et al., 2015). Smallholder farms directly employ about 175 million people (AGRA, 2014). With commercial farming largely concentrated in the cash crop sector, the dominance of smallholders in staple food production is in fact considerably higher. Small farms also contribute to economic growth, through production of several agricultural export commodities such as horticulture, cocoa, coffee, tea, rubber and palm oil. In several developing countries, such high-value export crops represent a high share of exports and of foreign earnings. Several of these export commodities are to a large extent smallholder-based, such as horticulture exports in Madagascar and Senegal, cocoa in Côte d'Ivoire, and coffee in Ethiopia (Maertens et al., 2012; Minten et al., 2009; Kuma et al., 2019). Overall, farm household systems in this region are believed to have great potential, and increasing their agricultural productivity is a potential way to improve food security and livelihoods for rural and peri-urban households (HLPE, 2013).

— The direct link between smallholders and rural food and nutrition security. Smallholder agriculture is embedded in rural livelihoods. As such, enhancing the production capacities and economic resilience of smallholders may improve food security and nutrition at various levels. According to Dialou et al. (2013), growth in smallholder agriculture may have significant direct effects on the livelihoods of the poor, through increasing food availability and incomes.

— The focus of national policies and donor assistance programmes on addressing the challenges faced by smallholder farms. Inspired by the arguments above, most country-level and international donor agricultural policies are specifically targeting smallholder farming. Smallholders face specific challenges and market failures. Therefore, improving the capacity and economic resilience of smallholders involves tackling an array of challenges, such as low levels of agricultural productivity; limited use of inputs and improved varieties; limited farm size; limited access to finance and capital; inadequate access to modern markets; food price volatility; and rising agriculture-related health risks and food insecurity (FAO et al., 2015). Policies and donor programmes focus on removing or reducing the challenges faced by small and family farms. They typically include programmes that aim to: (i) improve farmer access to agricultural inputs (mainly improved seeds and fertilizers); (ii) improve adoption of appropriate mechanization; (iii) improve access to financial markets (credit and insurance); (iv) improve provision of technical assistance services and capacity building; (v) facilitate use of agricultural knowledge and technologies; (vi) improve infrastructure (rural roads, storage facilities, market places, processing, etc.); (vii) improve dissemination of information regarding market conditions, etc. Several countries focus their agricultural policies on smallholders, emphasizing their relevance in increasing production, as well as in reducing hunger and food insecurity (e.g. Nigeria's Agricultural Promotion Policy 2016-2020; Ethiopia's Agricultural Development Led Industrialization). Some policies or programmes target the poorest subsistence farms, while other programmes are directed specifically at medium-sized farms that market a large share of their produce.

In addition to the fact that farm households are by far the dominant farming system in Africa, the availability of data also played a role in our decision. Household survey data provide detailed accounts of farming operations, outputs and costs. It is difficult to obtain similar, trustworthy data for large commercial farms that operate as businesses.

Although the microeconomic analysis of agricultural policies in sub-Saharan African in this study will focus on farm households, it should be emphasized that the sample of farm households does not only include small, subsistence farms. Our model relies on data from the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS–ISA), which provide a national representative survey of the rural population, with a focus on the farming sector. Farm size ranges from < 0.1 ha up to 5 ha in Ethiopia, where farm size is typically very low, up to approximately 25 ha in Tanzania, Côte d'Ivoire and Senegal. A few farms in the sample even operate up to 50 ha of land or more. Thus, our model includes small, medium and large farms, and subsistence farms as well as farms that are completely market-oriented, so it does represent the whole distribution of farm households in the African countries surveyed. As such, our model can assess how selected relevant policies will affect small vs large farms, and who will benefit from subsidized programmes.

Our current model does not cover farms that are operated by cooperatives or as large private businesses. Besides the issue of data availability for such large farms, it is also difficult to argue that they have the same objective function, and follow the same decision structure, as farm households. It is thus hard to propose a model that correctly simulates agent behaviour in both cases. For example, while farm households typically consume part of their own produce, and rely mostly on family labour for at least part of the year, this scenario does not fit the decision model of large agricultural businesses.

Based on the arguments above regarding the importance of farm households in African agriculture and agricultural policies, we believe that in most of the situations and policy simulation exercises, our farm household approach provides sufficient coverage of the agricultural sector, and that the distribution of small and large farms within our data will provide the necessary policy insights. Nevertheless, we acknowledge that our model may need to be adjusted for policies affecting specific crops frequently operated by large commercial estates, or for policies that specifically address large companies.

In the case of simulation exercises where large commercial businesses or cooperatives cannot be neglected, we consider several potential solutions. One possibility involves creating a 'virtual' large commercial farm to represent that part of the agricultural sector that is missing. Even though individual farm data may not be available for such large commercial farms, ad hoc surveys may provide data to represent such a farm type.

3 Motivation for the use of farm household optimization models

The unit of our micro-level analysis is the farm household, which is key to African agriculture – as argued above. Farm household models represent only a fraction of microeconomic research on rural economies. They are often applied to family-run or peasant agriculture, where production, labour allocation and consumption decisions are linked due to market imperfections (de Janvry et al., 1991; Taylor and Adelman, 2003). When markets are perfect, households are indifferent as to whether they consume their own-produced food or market-purchased goods. Production and consumption decisions are then defined as separable, and consequently the optimization programme resulting from such a household model can be solved recursively. However, if a household faces market failures, separability no longer holds and the household's production and consumption decisions must be solved simultaneously (Singh et al., 1986).

Originally, farm household models were designed as tools for price policy analysis (Taylor and Adelman, 2003). They were applied to analyse several issues, such as food demand and nutrition (Strauss, 1986); labour supply choices (Barnum and Squire, 1979; Dawson, 1984; Goodwin and Holt, 2002); consumption–investment interaction (Phimister, 1995); and the impact of agricultural productivity crises (Jayachandran, 2006).

According to the literature, three alternative behavioural assumptions are used to investigate household behaviour. These focus on the following hypotheses, related to the household's objective function (Mendola, 2007): (i) 'profit-maximizing' (Schultz, 1964); (ii) 'utility-maximizing' (Chayanov, 1966; Sadoulet and de Janvry, 1995; Singh et al., 1986); and (iii) 'risk aversion' (Mas-Colell et al., 1995; Morduch, 1999; Roumasset, 1976). Within each theory, three major approaches have been applied to address the issue: (i) reduced form equation; (ii) a system of structural equations (e.g. structural econometric models); and (iii) mathematical programming. The choice of one or another of the three approaches largely depends on three elements: data availability, model focus and research scope.

Kuiper (2004) argues that in order to address specific research questions, it may not be necessary to estimate a complete household model, and the first approach can be followed. Reduced form equations can be derived from the first order conditions of the household maximization programme, describing how endogenous variables relate to an exogenous variable of interest (Paolisso et al., 2002; Woldenhanna and Oskam, 2001).

If more than one endogenous variable is of interest, the whole system of structural equations for the household model needs to be estimated using econometric methods (second approach). As an example of structural econometric models, we could look to the behavioural microsimulation models used for tax incidence, redistribution and poverty analysis (Spadaro, 2007). The main advantage of this approach is its fully empirically-based simulation behaviour, as well as its ability to test for underlying behavioural assumptions (Gocht and Britz, 2011). It also offers a flexible and theoretically consistent specification of the production technology, and allows us to test the relevance of parameters, given an adequate dataset (Howitt, 2005).

However, it is challenging to estimate a household model using the first two approaches (i.e. reduced form or system of structural equations). Firstly, the structure of the household model may be too complex to derive a limited number of equations. Secondly, econometric estimation may be hindered by unobservable variables. Such cases can occur, for example, when households produce commodities for home use only and not for market sale. Thirdly, econometric estimation sets requirements in terms of the number of observations needed, time horizon and variation in variables (Kuiper, 2004). Another important drawback is that only changes in existing policies, accounted for in the estimation phase, can be simulated. By consequence, they are inappropriate for *ex ante* assessment of the impacts of policy reforms based on 'new' instruments which have never been used before, or when limited data are available. The other serious disadvantage of these structural econometric models is the lack of explicit description of the technology, because input demand cannot generally be allocated to production activities. This makes it difficult to link the results of such models to biophysical models, which are useful for assessing the environmental impacts of agricultural systems, for instance.

The third approach, based on mathematical programming (i.e. optimization) (Kantorovich, 1939; von Neumann, 1947; Dantzig, 1963), involves solving a general maximization (profit or utility) problem, subject to a set of constraints representing production technology, resource endowments and policy restrictions. Since the household is assumed to maximize a utility function, mathematical programming techniques offer an appropriate alternative.

The model used for this project relies on this last approach, for the following reasons.

(i) It allows explicit representation of decision behaviour and technology adoption.

(ii) It enables modelling of complex policy constraints under which behavioural functions cannot be derived easily, if at all, under the two previous approaches (Heckelei and Wolff, 2003).

(iii) It is flexible in terms of incorporating policy, economic, nutritional and environmental constraints.

(iv) Contrary to econometric approaches, which are limited to *ex post* analysis of policies/technologies for which past observations are available, mathematical programming is suitable for both *ex post* analysis and the appraisal of new technological/policy options (*ex ante*).

(v) Data requirements for running a mathematical programming model are not excessive, compared to other approaches. In many cases, analysts are required to construct models for systems where time series data are absent, or are inapplicable due to structural changes in a developing or shifting economy (Howitt, 1995).

(vi) It has been extensively tested/applied in the literature in the context of agricultural policy modelling, including in developing countries.

A literature review shows an increasing number of farm household programming models being used to address a multitude of questions. McGregor et al. (2001) reviewed all studies using these type of models up to 2001. In 2007, Janssen and Van Ittersum (2007) provided an excellent review of applied farm bio-economic models in developed countries, including some farm household models. More recently, van Wijk et al. (2014) provided a literature review of farm household models, with an emphasis on those focusing on food security in a changing climate. Here, we review the more recent ones used in developing countries, comparing the methodology used, their geographical coverage and the underlying behavioural considerations, using the information published in papers (Table 1).

Table 1. Overview of recent applied farm household programming models in developing countries [(1)]

Reference	Region of application	Farm heterogeneity	Simulated scenarios	Model Type	Time	Risk & uncertainty	Objective function	Household Consumption	Market imperfection	Household prices
Komarek et al (Komarek et al., 2014)	North-east Gansu Province, China	4 farm household types	China's Sloping Land Conversion Program (SLCP)	MIP	Static comparative	–	Net present value of net total household income	–	–	Exogenous
Gibreel et al. (Gibreel et al., 2014)	South-west China	2 farm household types	A business as usual scenario (BAU)	LP	Dynamic		Farmers' net income	Minimum consumption requirement	Labour market	Exogenous
Sanfo and Gerard (Sanfo and Gérard, 2012)	Plateau Central region of Burkina Faso	3 farm household types	Public goods policies	NLP	Dynamic	Market and climate risks	Mean-variance utility function	Minimum consumption requirement	Product, labour and capital markets	Exogenous
Gill (Gill, 2010)	Western Kenya	4 farm household types	HIV/AIDS upon food security	LP	Dynamic	Market risk	End-of-year cash		Perfect market	
Laborte et al. (Laborte et al., 2009)	Northern Philippine	4 farm household types	New technologies	LP	Static comparative	Market risk	Discretionary Income		Labour and credit markets	
Yiridoe et al. (Yiridoe et al., 2006)	Northern Ghana	1 farm household type	Alternative rice cropping systems	LP	Static comparative	–	Total gross margin		–	
Van den Berg et al. (van den Berg et al., 2007)	Zhejiang province, China	3 farm household types	Increasing farm size and mechanization	LP	Static comparative		Farm income		Perfect market	
Dolisca et al. (Dolisca et al., 2009)	Haiti	2 farm household types	Alternative deforestation solution	LP	Static comparative		Net income	–	–	
Holden et al. (Holden et al., 2004)	Ethiopian highlands	3 farm household types	Better access to off-farm income	NLP	Dynamic	Drought risk	Discounted utility	Quadratic expenditure system	Labour market	Endogenous (Labour)
Ruben and Van Ruijven (Ruben and van Ruijven, 2001)	Southern Mali	1 typical farm household	Effects of agricultural policies	NLP	Static comparative	–	Expected utility of consumption	–	Labour, capital and animal traction markets	Exogenous

([1]) – : not included or not explicitly specified; MIP: mixed integer programming; LP: Linear Programming; NLP: Non-Linear Programming.

Source: Our elaboration

As shown in Table 1, there is significant diversity across models with respect to research questions, geographical coverage and assumptions. However, most of the models reviewed are based on linear programming, and thus cannot exactly reproduce the observed situation. In addition, they use exogenous household prices and therefore cannot endogenously capture the effects of transaction costs on market participation decisions. Moreover, in most of these models, household consumption is modelled through a minimum consumption constraint, which does not allow household consumption decisions to be captured accurately.

The model used for this research project relies on mathematical programming – more specifically, positive mathematical programming (Howitt, 1995) – which is able to overcome the above issues. It also features a consumption function parameterized through Bayesian estimation. Another novelty of this type of model is that, because of the assumption of non-separability (between farm and household decisions), the price at which the household values a commodity is generated by the model (i.e. endogenous within a price band); it depends on the household trading status. The non-separability issue was already taken into account in previous studies, such as Kruseman et al. (1995) and Ruben and van Ruijven (2001); in these studies, however, prices were often assumed to be exogenous.

4 The FSSIM-Dev model

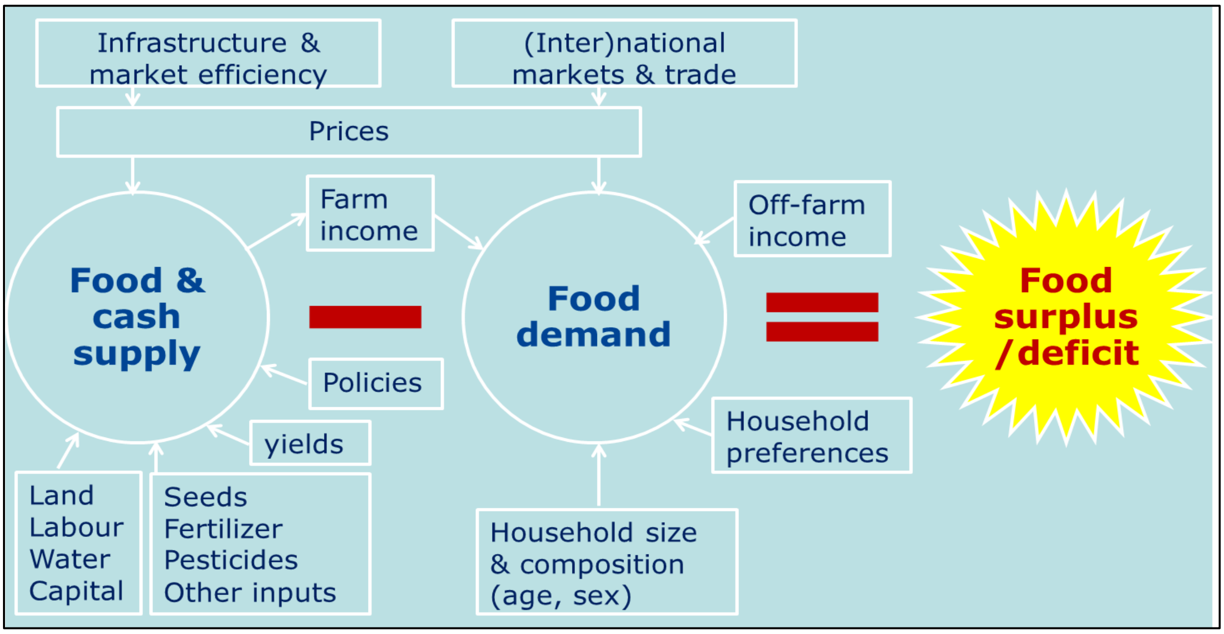
4.1 General description of the model

FSSIM-Dev is a micro-simulation tool designed to assess policy impacts on food security and rural poverty alleviation, in the specific context of low-income/developing countries. It aims to inform policymakers as to how changes in prices, technology, food and agricultural policies might affect the viability and food security of heterogeneous sets of farm households that characterize the agricultural sector. It also indicates which types of farm households will be most affected, where these most-affected farms are located, etc. FSSIM-Dev is an in-house (JRC D4: Economics of Agriculture Unit) extension of the FSSIM model, which was developed within the SEAMLESS consortium (Framework Programme for Research and Technological Development) to assess the impacts of agricultural and environmental policies on farm performance across Europe (Louhichi et al., 2010). The first version of the FSSIM-Dev model was used to assess the impacts of seed policies in Sierra Leone (Louhichi et al., 2013; Louhichi and Gomez y Paloma, 2014). This report presents the new version of the model (which is much more advanced and sufficiently flexible), and the results of its application to three countries in sub-Saharan Africa.

FSSIM-Dev is designed for analysis of family or peasant agriculture, where farm household production, consumption and labour allocation decisions are non-separable due to market imperfections. (In particular, information is not equally shared among stakeholders; resources, including labour, are not always mobile; and farms can hardly exit or enter the market without costs.) Peasants are farm households, with access to a piece of land and utilizing mainly household labour in farm production. They are characterized by partial engagement in markets, which are often imperfect or incomplete due to transaction costs (Ellis, 1992). Peasant farms have a dual character as both production and consumption units: a proportion of the produce is sold to meet their cash requirements and financial obligations, and a part of it is used for self-consumption. If the self-produced food is not enough for the family's subsistence, the peasant must turn to the market to fill the gap.

The farm household's production decisions depend on their consumption requirements, resource endowment, agro-ecological conditions, socio-economic contexts and policy environments. Meanwhile, their consumption decisions are assumed to be mainly driven by the income generated from farming activities, off-farm income, the number of household members and their preferences. Both production and consumption sides heavily depend on local prices, which in turn are affected by international markets and trade, infrastructure and market efficiency (Figure 1). This dual character of farm households, as producers and consumers, has the important implication that an increase in commodity prices drives both positive income and negative consumption effects.

Figure 1. Simplified diagram of the FSSIM-Dev model



Therefore, FSSIM-Dev aims to capture this dual nature of peasant households, as well as other key features of developing countries' agriculture, such as: (i) the interaction among farm households for market factors (e.g. labour and land); (ii) the heterogeneity of farm households with respect to both their consumption baskets and their resource endowments; (iii) the inter-linkage between transaction costs and market participation decisions; and (iv) the seasonality of farming activities and resource use.

FSSIM-Dev is a static, deterministic and (non-linear) positive mathematical programming (PMP) model. Static means that the model optimizes an objective function for one period (e.g. one average base year) over which decisions are taken; thus it does not explicitly account for time. Deterministic implies that the model does not deal with risk in the decision-making process. To focus on the role of transaction costs, we opted for a static model that implicitly represents risk preference through the behavioural function. However, at a later stage, risk related to yield and price variations will be explicitly incorporated, and therefore the behavioural assumption will be that farmers are utility maximizers, rather than just profit/income maximizers. Positive means that the model aims to reproduce the real situation (i.e. system) as accurately as possible, and to simulate 'what is likely' to happen to this situation when external conditions change (i.e. exogenous shocks). Given the multiplicity of PMP methods, the method has been selected based on multiple observations (cross-sectional data) and prior information on supply elasticities from the literature. The main advantage of the selected method is that it can not only exactly reproduce the observed situation — as most PMP methods do —but also ensure that the estimated farm dual values and the estimated own-price supply elasticities are as close as possible to the prior information (Louhichi et al., 2018).

Farm household models may be implemented either at individual farm household level (single) or at farm type level (group). In the former, individual (real) farm households are modelled. In the latter, farm households are clustered into relatively homogenous groups, and a representative (average or aggregated) farm is created for each group. These created (virtual) farm types are then modelled.

While farm type models are less demanding in terms of data and computation time, their main disadvantage is that farm heterogeneity is significantly reduced compared to individual farm level models. Farm households are so heterogeneous in their reaction to economic and policy incentives that it is hard to provide a detailed representation of policy effects through a set of farm type models.

Individual farm behavioural models are more appropriate for microeconomic analysis than farm type models, as they provide more detailed insights into the impacts of policy changes. Firstly, they offer more in-depth analysis of the results. They may provide simulations of policy impacts at individual farm level, as well as mean and standard deviation effects across the rural population. As such, they allow us to capture policy effects at the level of individual production/consumption units, as well as distribution across farm households. Secondly, they enable the flexible aggregation of results. Depending on the relevant farm characteristics and research focus, the policy effects can be aggregated by farm size, geographical location, socio-economic segment of society, etc. This flexibility makes individual farm models especially useful for policy impact analysis.

These advantages do come at a cost. The main limitations of individual farm household models are their high data needs and heavy computational requirements. As they require detailed information at individual farm level, parameterization and calibration are also more challenging than for farm type models.

For the purposes of this study, given the (recent) availability of detailed farm household survey data, and the large heterogeneity across farm households in Africa, we opt for a model operating at the level of the individual farm. Careful controls have been set on data quality and optimal computational processing, with the aim of reducing the time needed for calibration and computation as far as possible.

Considering all these specifications, FSSIM-Dev is in a position to provide a detailed assessment of agri-food policy impacts on a wide range of indicators, covering changes in land use, animal numbers, crop and animal production, household consumption, farm household income, government expenditure, poverty gap, and food security. These indicators are calculated at farm household level, but can easily be aggregated at any dimension relevant for the policymaker if the selected farm household sample is representative. However, these results should not be considered as projections or forecasts, but as indications of trends triggered by exogenous shocks.

Table 2 summarizes the main specifications of the FSSIM-Dev model. At this stage, the model is only implemented for the arable sector.

Table 2. Main features of the FSSIM-Dev farm household model

Model name	Farming System Simulator for Developing Countries (FSSIM-Dev)
Institution responsible for development and maintenance	JRC Economics of Agriculture Unit (in-house model development and maintenance), in cooperation with DG DEVCO C1 Unit
Type of model	Individual farm household model, running for each single farm household in the sample (LSMS-ISA, Agricultural Sample Survey – AgSS, ad hoc survey, etc.)
Methodology	Static, deterministic and non-linear programming model
Model Calibration	Calibrated for a single year using positive mathematical programming (PMP)
Objective function	Farm household income maximization: Agricultural income + Value of tradable factors rented out + Off-farm income Agricultural income: Revenues – Accounting costs – Value of tradable factors rented in – Implicit costs (PMP terms)
Farm revenues	Value of sold and self-consumed quantities of goods
Farm accounting costs	Operating costs per unit for each production activity
Constraints	
Land	Sum of area by activity (crops, livestock) should be less than or equal to total farmland endowment defined by type of use (arable, pasture, irrigable land, etc.)
Labour	Sum of labour requirement by activity (crops, livestock) should be less than or equal to total farm labour availability defined by type of labour (men, women, etc.) and skills
Capital and risk behaviour	Captured by PMP terms
Consumption	Linear expenditure system (LES)
Price bands for goods	The price at which the household values a commodity is endogenous within a price band, based on market price (pm) and multiplicative transaction costs (t).
Complementary slackness conditions	For any goods, a farm household uses its own internal shadow price if and only if it does not participate in the market for those goods.
Market clearing conditions	Sum of production plus market demand for each good must be equal to consumption plus market sales.
Livestock	Animal demography and livestock constraint, balancing feed demand and feed supply
Other considerations	
Yield and nitrogen fertilizer rate by activity	Endogenous variables through yield response function to nitrogen fertilizer
Other input costs by activity	Exogenous variables
Total farmland	Fixed at base year level

endowment	
Structural change	No
Market interaction	No input and output market interactions (at this stage – 2020)
Changes in management practices	Yes, using a combination of continuous approach for nitrogen fertilizer and a discrete approach for other inputs (seeds, pesticides, etc.)
Time horizon	Varies across country
Potential scenarios	Market price support, production subsidy, input subsidies, income policies, social transfer, public investments, producer price change, high/low/volatile food prices, alternative cropping systems/technologies, etc.
Model results	
Type of model results	Production, land use, land allocation among activities within the farm, extensification/intensification level, agricultural income, farm household income, variable costs, distribution of farm household income among farmers, gainers and losers from policies, poverty gap and food indicators, Gini index, etc. for each scenario (base year(1), baseline(2) and policy scenarios)
Farm household level	Single farm household units
Farm group aggregation	By specialization, economic size, market orientation or other relevant dimension
Regional aggregation	Village, region, district and country (depending on the dataset available)
Data needs	
Data	LSMS-ISA data, AgSS, farm household data collected ad hoc
Software and programming language	
Programming language	The model is developed in the General Algebraic Modelling System (GAMS) and linked to a Graphical User Interface application that is built using Java.

(1) Base year refers to the year for which FSSIM-Dev is calibrated.

(2) Baseline is interpreted as a projection over time of key variables representing development of the agricultural sector, in terms of technological, structural and market changes, before the implementation of the policy to be simulated. It represents the reference for analysis of the impact of the selected policy scenarios.

Source: Our elaboration

4.2 Mathematical structure and formulation

FSSIM-Dev is a constrained optimization model which relies on both the general household's utility framework and the farm's production technical constraints, in a non-separable regime. The approach of Singh et al. (1986) assumes that the farm household maximizes its utility from the consumption of goods, which may be purchased or home-produced, subject to production function, time and cash constraints (Singh et al., 1986: Sadoulet and de Janvry, 1995). Contrary to this, FSSIM-Dev maximizes a utility function which depends on the production of goods, which may be sold or home-consumed, subject to consumption function, time and cash constraints. In line with Shiferaw and Holden (1999), farm household income is used as a proxy for the utility function. Therefore, FSSIM-Dev maximizes farm household income subject to resource endowment, consumption and cash constraints. We describe these aspects in detail below.

The general formulation of the model is as follows.

Max *Farm household income* (1)

Subject to:

- *Resource endowment constraints*
- *Consumption function (linear expenditure system - LES)*
- *Market participation decisions: price bands and complementary slackness conditions*
- *Market clearing conditions*
- *Cash constraints*

An identical model structure was applied to all farm households modelled, to ensure uniform handling of all the individual farm household models and their results (i.e. the farm models have the same structure of equations and variables, but the model parameters are farm household–specific). No cross-farm constraints or relationships are assumed in the current version of the model. That is, the equations aiming to capture the interaction between farm households for tradable factors – land and labour – are switched off, due to data limitations for their calibrations. The estimation phase for the behavioural function parameters represents an exception to the above; in this phase, all individual farms in each region are used simultaneously to estimate these parameters.

4.2.1 Farm household income maximization

The expected income (*R*) of the farm household (*h*) to be maximized is defined as the income earned from all economic activities by family members of the same household. It has three components: expected agricultural income (π), income from marketed factors of production (Ψ) and off-agricultural incomes (*exinc*).

$$\textbf{Max } R_h = \pi_h + \psi_h + exinc_h \tag{2}$$

Agricultural (farm) income is defined as income earned by households through work time devoted to farming activities. Income from marketed factors of production includes non-farm wages and rented-out land and machinery/tools; it is calculated as follows:

$$\psi_h = \sum_{tf} s_{h,tf}\, p_{h,tf}$$

where *tf* indexes tradable factors, *s* is the vector of rented-out tradable factors and *p* their prices.

Off-farm incomes are defined exogenously and can originate from different sources, such as self-employment activities (petty trading, craftsmanship, etc.), pensions, transfers (including remittances) and donations. They exclude wages derived from the employment of family labour in non-farm activities (which are included in income from marketed factors of production).

Agricultural (farm) income (π) is represented by a Leontief-quadratic function, which combines a Leontief gross margin (*gm*) function and a quadratic activity-specific behavioural function. Gross margin function is defined as total revenue from agricultural activities – including sales, self-consumption and production subsidies (where relevant) – minus the value of tradable factors rented-in and the variable accounting costs of production activities. The accounting costs include costs of seeds, fertilizers, crop protection and other specific costs. The quadratic activity-specific function is a behavioural function introduced to calibrate the farm model to an observed base year situation, as is usually done in PMP models. This function intends to capture the effects of factors that are not explicitly included in the model, such as price expectations, risk-averse behaviour, capital and crop rotation constraints, and other unobserved costs (Heckelei, 2002).

$$\pi_h = gm_h - \sum_i (d_{h,i} + 0.5Q_{h,i,i'} x_{h,i}) x_{h,i} \tag{3}$$

$$gm_h = \sum_j (s_{h,j} + cs_{h,j}) p_{h,j} + \sum_i sb_{h,i} x_{h,i} - \sum_{i,k} a_{h,i,k} x_{h,i} - \sum_{tf} b_{h,tf}\, p_{h,tf} \tag{4}$$

$$q_{h,j} = \sum_i y_{h,i,j} x_{h,i} \tag{5}$$

where indices *i*, *j* = 1,2,..., *I* denote the agricultural (crop and livestock) activities and products; (3) *k* = 1,2,..., *K* are intermediate inputs (fertilizer, seeds, crop protection, etc.), and *tf* = 1,2,..., *M* are the tradable factors. *p* is the (n×1) vector of expected prices for goods *j* and tradable factors *tf*; *q* is the (n x 1) vector of produced quantities of goods; *s* is the (n×1) vector of sold quantities of goods or rented-out tradable factors; *cs* is the (n×1) vector of self-consumed quantities of goods; *y* is the (n×1) vector of (crop and animal) yields; *x* is the (n×1) vector of the non-negative levels of the agricultural activities *I*; *sb* is the (n×1) vector of production subsidies; *a* is the (n×k) matrix of variable accounting costs for intermediate input *k* and activity *I*; *b* is the (n×1) vector of bought quantities of goods or rented-in tradable factors; *d* is the (n×1) vector of the linear part of behavioural activity function; and *Q* is a (n×n) symmetric, (semi)positive matrix of the behavioural activity function for the activities. *Q* and *d* are estimated using a variant of the PMP approach.

It is important to note that the introduction of a Leontief production function for variable input costs independent from the quadratic behavioural function presents some advantages: (i) it provides an explicit link between production activities and total physical input use; (ii) it eases linkage to environmental indicator calculation; and (iii) it allows simulation of policy measures linked to specific farm management. Its main limitation is the lack of rationalization (Heckelei and Wolff, 2003), as intermediate input uses are assumed to be independent of the (unknown) marginal costs captured by the quadratic behavioural function (Louhichi et al., 2018).

The second drawback of the Leontief production function is the rigid technology assumption. One could expect that an increase in a crop share would change average soil quality, which in turn should change yields and nutrient requirements. To relax this assumption, several production techniques with different intensity levels are specified for each crop and introduced in the model.

For some model applications and where data are available, for instance in the Ethiopian and Tanzanian case studies, a crop-specific quadratic yield response function to nitrogen fertilizer (considered the most important nutrient in SSA) was also econometrically estimated. This was then calibrated to the observed level and embedded in the model, under the assumption that yields are independent of acreage planted. This yield response function allows a better representation of the behaviour of the farm household, which could easily adapt its nitrogen fertilizer use to the physical (climatic and soil) and economic (market and policy) context. It also enables recommendations on fertilizer rates to be made under different policy options.

This estimation of the crop yield response function is based on the following equation:

$$y = \alpha N + \beta N^2 + \gamma \tag{6}$$

Where *y* is the crop yield (kg/ha); *N* is the nitrogen application rate (kg/ha); and α, β and γ are the coefficients of the regression model. The coefficients α, β, and γ are crop, seed variety, season and region-specific to reflect technological, soil and climate heterogeneity. γ is the intercept parameter whose position (value) can be shifted up or down in the calibration step to capture farm specificities.

(3) To simplify mathematical notations, we assume one product per activity so that indices for activity and product are identical.

In such cases, the other fertilizer elements (phosphorus, potassium, etc.) are assumed to be applied in fixed proportions to nitrogen, and remaining inputs such as pesticides and labour are assumed to be independent to nitrogen fertilizer and used at a fixed rate per hectare for each specific crop.

4.2.2 Resource endowment constraints

Resource endowment constraints are the ones usually faced by farm households when making production and optimization decisions. The most common ones are land and labour, and in some instances physical and financial capital constraints. In the current FSSIM-Dev model, only land and labour are explicitly modelled. All other constraints are captured through the implicit cost function. Land constraint is defined by land category: arable land and permanent pasture (grassland). Arable land and permanent pasture are treated as fixed endowments; their corresponding levels for each individual farm household are derived from the survey data. This means that there is no allowance for increase or decrease in these lands, or for the conversion of arable land into pasture or vice versa. The assumption of fixed land, or non-substitutability between arable and pasture, is explained by the short to medium term of our analysis; also because in most SSA countries, intra- and inter-farm adjustments in land use are often impeded by natural constraints, customs, imperfections in/lack of land market, etc. Within each land category, activities are assumed to be fully substitutable.

The arable land is divided into two classes: rainfed and irrigable land. Due to data limitations, the irrigable land is assumed to be equal to the area of current irrigated crops (i.e. assuming binding constraints), and the rainfed land is the difference between the total arable land and the irrigable land.

Besides land, labour is the most important asset, but also the main constraint for most farmers in SSA countries. Beyond crop and livestock production, labour is primarily needed for domestic purposes. Seasonal calendars for crop and livestock management also feature a diverse range of tasks. As an addition to the household labour endowment, the capacity to hire labour plays a key role in meeting farm-household labour needs.

To account for all these specificities, the labour constraint is defined in FSSIM-Dev according to season and task category. Household labour endowment is assumed to be fixed, and although farm households may theoretically vary the amount of labour they supply to or demand from the labour market, the total amount of labour in the (local) economy in which the farm household is embedded is assumed to be fixed in the short term. This leads to an endogenously determined rural wage which, for the sake of simplicity, is assumed to be equal for all households. Households choose how much labour to use for production, either drawing from their own labour resources or hiring from other households. Both types of labour are assumed to be freely substitutable, and the marginal value of household labour is equal to the rural wage.

Labour and equipment are assumed to be tradable factors and can be exchanged among farms within the same region (or district or village). Any surplus of labour can be supplied outside the agricultural sector at market prices. Conversely, any surplus of demand for labour can be satisfied by importing from the market. Thus, labour requirements can be served either by family labour endowments or by hiring external labour.

$$\sum_{tf} A_{h,i,tf}\, x_{h,i} \leq B_{h,tf} + b_{h,tf} - s_{h,tf} \quad \left[\rho_{h,tf}\right] \tag{7}$$

$A_{f,i,m}$ is the (n×m) matrix of resource requirements (land, labour, etc.); b is the (n×1) vector of bought quantities of goods or rented-in tradable factors; s is the (n×1) vector of sold quantities of goods or rented-out tradable factors; $B_{f,m}$ is the (m×1) vector of available resource levels; and $\rho_{h,m}$ are their corresponding shadow prices.

4.2.3 Consumption function

Many efforts have been made to describe household consumption behaviour, and various functional forms have been proposed in the literature that satisfy theoretical conditions of demand theory. Three of these have received considerable attention because of their relative empirical usefulness. They are the Linear Expenditure System (LES) developed by Stone (1954), the Almost Ideal Demand System (AIDS) developed by Deaton and Muellbauer (1980), and the combination of these two systems into a Generalized Almost Ideal Demand System (GAIDS) proposed by Bollino (1987). Other complete demand systems proposed in the literature, but not as widely used as the previous three, are the Rotterdam model by Theil (1976, 1965) and Barten (1964) and the translog model (Christensen et al., 1975).

In FSSIM-Dev we opted for the Linear Expenditure System (LES), which is the system most frequently used for empirical estimation of consumer demand. It is also the easier in terms of parameterization and calibration. In this system, the set of demand functions is expressed in expenditure form and assumed to be linear for all prices and incomes as follows:

$$c_{h,j}\ p_{h,j} = \delta_{h,j}(Y_h - \sum_{j'} \upsilon_{h,j'} p_{h,j'}) + \upsilon_{h,j} p_{h,j} \tag{8}$$

$$\begin{cases} 0 \le \delta_{h,j} \le 1 \\ \sum_j \delta_{h,j} = 1 \\ \upsilon_{h,j} \le c_{h,j} \end{cases}$$

where p is the (n x 1) vector of prices of goods; c is the (n x 1) vector of consumed quantity of goods; Y is the farm household 'full' income, υ is the uncompressible consumption (interpreted as minimum subsistence or 'committed' quantities below which consumption cannot fall); and δ is the marginal budget share ($\partial pc/\partial Y$). $\sum_{j'} \upsilon_{h,j'} p_{h,j'}$ is the subsistence expenditure and the term $(Y_h - \sum_{j'} \upsilon_{h,j'} p_{h,j'})$ is generally interpreted as 'uncommitted' or 'supernumerary' income, which is assumed to be spent in fixed proportions δ between commodities (Sadoulet and de Janvry, 1995).

The unknown parameters υ and δ are estimated simultaneously for each region, using the highest posterior density (HPD) estimator (Heckelei et al., 2008) and prior information on income elasticities and Frisch parameters (see section 4).

As shown in equation (6), the 'full' income is the unique link between the producer and consumer side of the farm household. This income results partly from the solution to the producer problem (i.e. farm income), complemented by income earned from grants, pensions, transfers (including remittances) and donations (i.e. off-farm incomes), plus the total value of household endowments of factors (Sadoulet and de Janvry, 1995). The 'full' income of the household is equal to the total value of the household's endowments of factors:

$$Y = R + \sum_{tf} B_{h,tf}\, p_{h,tf} \tag{9}$$

$$R_h = \pi_h + \psi_h + exinc_h \tag{10}$$

4.2.4 Price bands and complementary slackness

In addition to deciding how much of each good j to produce q_j and to consume c_j, the farm household also decides, for each produced good q_j, whether to participate in the market, and the quantity of each good to market (i.e. to sell s_j or to buy b_j). Market participation decisions depend on several factors, including transaction costs, market prices, government support services, available incomes, household endowments and household demographic characteristics.

FSSIM-Dev involves three blocks of equations for modelling market participation decisions.

— The first block defines the upper and lower bounds of farm household commodity prices. The upper bound for each good j is determined by the market price (p^m) multiplied by the buyer transaction cost factor (t^b). The lower bound is similarly determined by the market price multiplied by the seller transaction cost factor (t^s).

$$p_j^m t_{h,j}^s \le p_{h,j} \le p_j^m t_{h,j}^b \ ; \ p_{tf}^m t_{h,tf}^s \le p_{h,tf} \le p_{ft}^m t_{h,tf}^b \tag{11}$$

— The second block of equations, known as complementary slackness conditions, states that a farm household uses its own internal shadow price if and only if it does not participate in the market for goods.

$$s_{h,j}\ (p_{h,j} - p_j^m t_{h,j}^s\ ) = 0\ ;\ b_{h,j}\ (p_{h,j} - p_j^m t_{h,j}^b\ ) = 0 \tag{12}$$

— The third expression is used to ensure that, for each commodity, a farm household can be either a buyer or a seller but not both (households can also be self-sufficient, i.e. neither buying nor selling goods).

$$s_{h,j}\ b_{h,j}\ = 0 \tag{13}$$

Agricultural commodity prices (i.e. market prices) (p^m) are exogenously fixed for households participating in markets. We assume that those farm households are price takers on commodity markets, and they are not in a position to influence the market prices. However, the price at which the household values a commodity will be generated by the model, depending on household trading status (net buyer, net seller or self-sufficient), which in turn is related to transaction costs.

Transaction costs are any costs that an agent incurs in order to perform a market transaction. They are caused by, for example, high transportation costs, poor infrastructure, non-competitive market structures, and incomplete information. A buyer facing transaction costs perceives the effective price of commodities he wants to buy as higher than the market price. Similarly, a seller facing transaction costs perceives the effective sale price as lower than the market price (Brooks et al., 2011). Due to these costs, production and consumption decisions become non-separable and conventional microeconomic theory is no longer suitable to model farm household behaviour (Henning and Henningsen, 2007). As this situation is very common in many low-income economies, FSSIM-Dev was designed to take transaction costs into account and to endogenously capture market participation decisions. This is achieved using the concept of price band, based on market price (p^m) and multiplicative (or proportional) transaction costs (*t*) (Sadoulet and de Janvry, 1995). As buyers of consumption goods, farm households face an effective buying price (p^m x t^b) that is higher than the market price ($t^b > 1$). As sellers, they face an effective selling price (p^m x t^s) that is lower than the market price ($t^s < 1$).

4.2.5 Cash constraint

Having transaction costs in the model requires that we explicitly express a cash constraint for farm households. Equation (7) states that expenditures on purchases of intermediate inputs, goods and tradable factors must not exceed revenues from sales of goods and tradable factors plus income earned from grants, subsidies, pensions, transfers (including remittances) and donations (i.e. off-farm incomes).

$$\sum_{i,k} a_{h,i,k} x_{h,i} + \sum_j b_{h,j}\, p_{h,j} + \sum_{tf} b_{h,tf}\, p_{h,tf} \le \sum_j s_{h,j}\, p_{h,j} + \sum_{tf} s_{h,tf}\, p_{h,tf} + \sum_i sb_{h,i} x_{h,i} + exinc_h \tag{14}$$

4.2.6 Market clearing conditions

FSSIM-Dev includes one market clearing condition, to ensure commodity balance at household level. This condition stipulates that the sum of production and market demand for each good must be equal to consumption plus market sales.

$$q_{h,j} + b_{h,j} = s_{h,j} + c_{h,j}\ \ ;\ \ c_{h,j}\ = b_{h,j} + cs_{h,j} \tag{15}$$

4.3 Model calibration

The aim of the calibration process is to ensure that the observed production and consumption decisions of the farm households during the base year period are exactly reproduced by the optimal solution of the programming model.

The calibration of FSSIM-Dev is performed in two steps: first the production decision is calibrated, then the farm income generated through this step is used to calibrate the consumption decision.

4.3.1 Calibrating production decision

The calibration of the supply side of the FSSIM-Dev model aims to replicate the two key observable production decision variables – 'nitrogen fertilizer applied to crop activities at plot level (i.e. by unit of area)' and 'land allocated to production activities at farm level' – by taking into account the underlying profit optimization problem. This is performed in two successive steps: first we calibrate the nitrogen fertilizer use, then the land allocation.

4.3.1.1 Calibrating yield response to nitrogen fertilizer

The calibration of yield response to nitrogen fertilizer consists of recovering the unknown farm- and crop-specific nitrogen fertilizer prices and the nitrogen response intercept to allow us to reproduce the observed yield exactly, and the observed nitrogen fertilization rate as closely as possible, in the optimal solution.

Mathematically, this consists of solving the following model, where the farmer's objective is assumed to be maximization of profit, by unit of area, over nitrogen cost:

$$\begin{aligned} &\max \pi_{h,j,t} = p_{h,j} y(N) - Pn_{h,j,t} N_{h,j,t} \\ &\text{s.t.} \quad y(N) = \alpha_{j,t} N_{h,j,t} + \beta_{j,t} N_{h,j,t}^2 + \gamma_{h,j,t} \\ &\qquad y(N) = y^0 \quad \left[\eta_{h,j,t}\right] \\ &\qquad N_{h,j,t} \geq 0 \quad \left[\mu_{h,j,t}\right] \end{aligned} \tag{16}$$

Where π is the farm profit by unit of area, *h* is the farm, *j* is the crop activity, *t* is the seed variety (e.g. improved vs traditional seeds), *y* is the crop yields (kg/ha^{-1}) and y^0 is its observed level in the base year (assumed to be optimal). *p* is the output prices; α, β and γ are the coefficients of the regression model; *N* is the nitrogen fertilizer applied (kg/ha^{-1}); *Pn* is the nitrogen fertilizer prices; η is the Lagrange multiplier for the constrained yield level; and μ is the Lagrange multiplier for the non-negativity constraints for *N*. Only α and β are region-specific; all the remaining parameters are farm-specific. By setting α and β at regional level, we assume that farms within the same region have a common technology and therefore they have the same yield curve shapes, although with different starting points (intercept γ is farm-specific).

The first-order conditions (FOCs) of model (16) can be rewritten as:

$$\begin{aligned} &(1) \quad \frac{\partial y(N)}{\partial N} = \alpha_{j,t} + 2\beta_{j,t} N_{h,j,t} - \frac{(pn_{h,j,t} - \mu_{h,j,t})}{(p_{h,j,t} - \eta_{h,j,t})} = 0 \\ &(2) \quad \mathrm{y}_{h,j,t} - \alpha_{j,t} N_{h,j,t} - \beta_{j,t} N_{h,j,t}^2 - \gamma_{h,j,t} = 0 \\ &(3) \quad N_{h,j,t} \mu_{h,j,t} = 0 \\ &(4) \quad \mu_{h,j,t} \geq 0 \end{aligned} \tag{17}$$

Assuming that the observed yields (y^0) are at their optimum levels, and the observed output prices (p^0) are accurately known, the next step seeks to estimate – using the HPD method (Heckelei et al., 2008) ([4]) – the unknown Lagrange multipliers, the farm- and crop-specific nitrogen fertilizer prices, and the farm- and crop-

([4]) This Bayesian approach was proposed by Heckelei et al. (2008) as an alternative to entropy methods for deriving solutions to underdetermined systems of equations. They argued that the main advantage of this approach is that it allows a more direct and straightforward interpretable formulation of a priori information available, and a clearly defined estimation objective.

specific nitrogen response intercept to allow us to reproduce these observed yields exactly, and the observed nitrogen fertilization rate as closely as possible, in the optimal solution.

The HPD approach for parameter estimation is carried out under the following assumptions.

- The observed yields (y^0) and output prices (p^0) are assumed to be accurately known (i.e. they are measured without errors).
- The farm-specific nitrogen fertilizer rate (N) is assumed to be observed with additive and normally distributed errors (e^N). For farmers declaring that they do not use nitrogen fertilizer, this rate is set to zero.
- The farm-specific nitrogen fertilizer prices (pn) are assumed to be observed with additive and normally distributed errors (e^p).
- The farm-specific nitrogen response intercept (γ) is assumed to be equal to the intercept for the regional yield response function, with additive and normally distributed errors (e^γ).
- The Lagrange multiplier for the observed yield constraint η is interpreted as the missing implicit price that guarantees that the observed yield (y^0) is at the optimum. η is assumed to be close to zero and the final price $P-\eta$ always positive.
- The error terms receive normal priors with zero mean, and variances equal to a fixed share of the observed value of the respective parameter $e \sim N(0,\sigma^2)$. Specifically, we assume that the variances of the errors are 20% of the observed value. This means that we assume that errors are independent and normally distributed with mean zero covariance matrix, such that three standard deviations cover 20% of the observed value of the related parameter (Jansson and Heckelei, 2011).

The general formulation of the corresponding HPD problem is now straightforward:

$$Min\ HPD_h = \left[\sum_{h,j,t} \frac{(e^N_{h,j,t})^2}{(\sigma^N_{h,j,t})^2} + \sum_{h,j,t} \frac{(e^P_{h,j,t})^2}{(\sigma^P_{h,j,t})^2} + \sum_{h,j,t} \frac{(e^\gamma_{h,j,t})^2}{(\sigma^\gamma_{h,j,t})^2} \right] \tag{18}$$

$$\alpha_{j,t} + 2\beta_{j,t} N_{h,j,t} - \frac{(pn_{h,j,t} - \mu_{h,j,t})}{(p^0_{h,j,t} - \eta_{h,j,t})} = 0 \tag{19}$$

$$\mathrm{y}^0_{h,j,t} - \alpha_{j,t} N_{h,j,t} - \beta_{j,t} N^2_{h,j,t} - \gamma_{h,j,t} = 0 \tag{20}$$

$$N_{h,j,t}\mu_{h,j,t} = 0 \tag{21}$$

$$\mu_{h,j,t} \geq 0 \tag{22}$$

$$N_{h,j,t} - N^0_{h,j,t} = e^N_{h,j,t} \tag{23}$$

$$Pn_{h,j,t} - Pn^0_{h,j,t} = e^P_{h,j,t} \tag{24}$$

$$\gamma_{h,j,t} - \gamma^0_{j,t} = e^\gamma_{h,j,t} \tag{25}$$

The equations (19) and (22) represent the FOCs for the optimization model (16). Equations (23) and (25) compute the error terms between the observed and estimated farm-specific fertilizer rate, price and intercept, respectively.

4.3.1.2 Calibrating production activity levels

The calibration of the land allocation consists of recovering the set of unknown parameters (*d, Q* and ρ), so that the optimization model as described in equations (2) and (15) exactly replicates the observed activity levels (x^0) of the base year. This is performed using a new variant of the PMP approach proposed by Louhichi et al. (2018).

Over the last decade, several PMP approaches have been developed to derive the parameters of the behavioural functions (*d* and *Q*) and to accurately calibrate programming models ([5]). However, as there are usually insufficient observations to allow a traditional econometric estimation ('an ill-posed' problem), most of the approaches proposed run without any type of estimation, by setting all off-diagonal elements of *Q* to zero and calculating the remaining parameters using ad hoc assumptions. To reduce the arbitrary parameter specifications, and more reliably estimate behavioural functions covering all the parameters, more recent applied programming models have either: (i) used exogenous information on supply elasticities (Britz and Witzke, 2014; Mérel and Bucaram, 2010) and/or on shadow prices of resources (Henry de Frahan et al., 2007); or (ii) estimated programming model parameters in an econometric sense, using either cross-sectional data (Heckelei and Britz, 2000; Heckelei and Wolff, 2003; Buysse et al., 2007; Arfini et al., 2008) or time series data (Jansson and Heckelei, 2011).

In this study, we use the PMP approach proposed by Louhichi et al. (2018), which relies on both multiple observations (cross-sectional data), and prior information on (i) supply elasticities ($\bar{\varepsilon}_r$) and (ii) dual values of constraints ($\bar{\rho}_{f,m}$), to calibrate the model to the base year condition. Supply elasticities are taken from the literature. Where prior information is unavailable, elasticities of 1 and 0.1 are used for annual crops and permanent crops, respectively. Prior information on dual values of resources (total and irrigable land and labour) are derived from the LSMS-ISA database.

The use of multiple observations (i.e. cross-sectional data) allows the model to estimate the full set of *Q* coefficients for crop activities, and to base the model specification on observed differences in behaviour. The use of exogenous information avoids arbitrary behaviour of the model in the simulation phase.

To perform the estimation, we derive the FOCs for the optimization model in equations (2) and (15), which are assumed to approximate farm household behaviour (Heckelei, 2002), and then apply the HPD method to estimate the unknown parameters (*d, Q* and ρ).

The HPD approach for parameter estimation is carried out under the following assumptions.

- The farm household prices, as well as the quantities of goods consumed, sold and purchased by farm households, are assumed to be equal to their observed levels.

- For each region, the HPD model minimizes the weighted sum of normalized squared deviations of estimated regional own-price (diagonal) supply elasticities, and farm-household dual values from their respective prior, subject to a set of data consistency (FOC) constraints.

- The normalized squared deviations of farm-household dual values are weighted with the proportion of the farm in the region, $\omega_h^{\rho} = w_h / \sum_h w_{fh}$, to obtain a weighted average normalized squared deviation at the regional level, where w_h is the farm-household weighting factor reflecting the number of farm households in the population represented by farm *h*.

- The normalized squared deviations of regional supply elasticities are weighted with the proportion of observed activity level in total regional land, $\omega_r^{\varepsilon} = N_r \, x_{i,r}^0 / \sum_i x_{i,r}^0$, to allow activities with a high proportion of area to dominate, where N_r is the number of observed crop activities (for $x_{r,i}^0$ > 0) in the region *r*.

- Prior information on dual values, $\bar{\rho}_{r,m}$, is set to the average land/labour rental prices at regional level. Large standard deviations for prior information are used to allow the data to dominate.

- The calibration to the exogenous supply elasticities is performed in a non-myopic way, i.e. we take into account the effects of changing dual values on the simulation response (Heckelei, 2002; Mérel and Bucaram, 2010).

([5]) For a review of PMP models, see Heckelei and Britz (2005); de Frahan et al. (2007); Mérel and Bucaram (2010); Paris (2010); and Heckelei et al. (2012).

- The estimated $B_{ft,i,i'}$ parameters related to the $Q_{f,i,i'}$ (see below) are common across farm households belonging to the same region and the same farm household type (group), *ft*. However, the $Q_{h,i,i'}$ parameters are activity- and farm-specific, owing to the farm-specific scaling factors, as suggested in Heckelei and Britz (2000). In other words, we exploit information contained in the cross-sectional sample to specify (farm household-specific) quadratic activity functions with cross-effects for production activities.
- The estimation of $B_{ft,i,i'}$ (and thus $Q_{f,i,i'}$) parameters relies only on observed activities, meaning that the well-known problem of self-selection is not explicitly addressed in this estimation. To cope with this problem, we adopted the following ad hoc modelling decisions ([6]) in the simulation phase: (i) in each region, the gross margin of the non-observed activities is equal to the farm-household type average gross margin; (ii) the activity's quadratic function parameter is equal to the activity's average quadratic function parameter within the farm-household type; and (iii) the linear term's quadratic function is derived from the difference between the gross margin and the dual values of constraints.
- In order to simplify the already complex estimation problem, the cash constraint is assumed to be unbinding, and thus its marginal value is equal to zero. Moreover, the non-negativity condition was omitted due to the heavy computational requirement. That is, all optimal activity levels are assumed to be positive. This implies that we may overestimate the profitability of non-observed activities.
- The exchange of land between farms is not allowed (i.e. assuming there is no land market).
- The general formulation of the corresponding HPD problem is now straightforward:

$$Min\ HPD_r = \left[\sum_{i,i'} w_r \frac{(\varepsilon_{r,i,i'} - \bar{\varepsilon}_{r,i,i'})^2}{\sigma^{\varepsilon}_{r,i,i'}} + \sum_{h,m} w_h \frac{(\rho_{f,m} - \bar{\rho}_{r,m})^2}{\sigma^{\rho}_{r,m}} \right] \tag{26}$$

$$gm_{h,i} - d_{h,i} - \sum_{i'} Q_{h,i,i'} x^0_{h,i'} - \sum_m A_{h,i,m} \rho_{h,m} = 0 \tag{27}$$

$$b_{h,m} - \sum_i A_{h,i,m} x^0_{h,i} = 0 \tag{28}$$

$$\varepsilon_{h,i,i'} = \left[Q^{-1}_{h,i,i'} - \sum_m (\sum_j A_{h,j,m} Q^{-1}_{h,i,j} (\sum_{j,j'} A_{h,j,m} Q^{-1}_{h,j,j'} A_{h,j',m})^{-1} \sum_j A_{h,j,m} Q^{-1}_{h,j,i'}) \right] \frac{gm_{h,i}}{x^0_{h,i}} \tag{29}$$

$$\varepsilon_{r,i,i'} = \frac{\sum_h w_h x^0_{f,i} \varepsilon_{h,i,i'}}{\sum_h w_h x^0_{h,i}} \tag{30}$$

$$Q_{h,i,i'} = \sum_{ht} \delta_{h,i} B_{ht,i,i'} \delta_{h,i'} \tag{31}$$

$$B_{ft,i,i'} = \sum_j Lb_{ft,i,j} Lb_{ft,i',j} \qquad Lb_{ft,i,i'} = 0 \quad for \quad i' > i \tag{32}$$

$$\sum_l Q_{h,i,l} Q^{-1}_{h,l,i'} = 1 \quad \forall i = i' \tag{33}$$

$$\sum_l Q_{h,i,l} Q^{-1}_{h,l,i'} = 0 \quad \forall i \neq i'$$

([6]) Different arbitrary assumptions were tested for setting the behavioural function's parameters for the non-observed activities, such as the use of the highest *Q* matrix, or the use of *B* matrix, but the results were not conclusive. In the end, we opted for this specification following methods often used in the literature.

where indices h denote farm households, ft farm-household type, r region and j, j' (similar to i, i') the agricultural activities and products. $gm_{f,i}$ is the gross margin for activity i; $Q_{f,i,i'}$ are the farm household-specific behaviour parameters; $\bar{\rho}_{r,m}$, $\sigma^{\rho}_{r,m}$ are the mean and standard deviation of the regional dual values of resource (land and labour rental prices) used as prior information; $\bar{\varepsilon}_{r,i,i}$, $\sigma^{\varepsilon}_{r,i,i}$ are the mean and standard deviation of regional own-price elasticities of supply used as prior information; and $\delta_{f,i}$ is a scaling factor with $\delta_{h,i} = \sqrt{1/x^0_{h,i}}$.

Prior information on dual values of constraints is assumed to be normally distributed with the means ($\bar{\rho}_{r,m}$) and standard deviations ($\sigma^{\rho}_{r,m}$) calculated at regional level using the farm weights. The standard deviation of regional elasticities ($\sigma^{\varepsilon}_{r,i,i}$) is assumed to be 50% of the mean.

The endogenous variables for the HPD problem defined in equations (17) to (24) are as follows: the dual values of resource, $\rho_{r,m}$; the farm-household price elasticities of supply, $\varepsilon_{h,i,i'}$; the regional price elasticities of supply, $\varepsilon_{r,i,i'}$; the behavioural parameters $B_{ft,i,i'}$ common across farm households belonging to the same region and the same farm type (group) ft; the elements of the lower triangular Cholesky decomposition related to $B_{ft,i,i'}$, $Lb_{ft,i,i'}$; and the farm household–specific behavioural parameters, $d_{f,i}$ and $Q_{f,i,i'}$ (including the inverse value $Q^{-1}_{f,i,i'}$).

The equations (27) and (28) represent the FOCs of the optimization model, for production activities and land constraint, respectively. Equations (29) and (30) compute supply elasticities at farm and regional levels, respectively ([7]). Equation (31) calculates the farm household–specific $Q_{h,i,i'}$ parameters for the behavioural function. Equation (32) is the Cholesky decomposition of B matrix, which ensures appropriate curvature properties for the estimated quadratic cost function (i.e. convex in activity levels). Finally, equation (33) calculates the inverse of farm household–specific $Q_{h,i,i'}$ parameters.

The estimated parameters in equations ((26) to (33)) guarantee reproduction of the actually observed production activity levels (x^0) when the model (equations (2) and (15)) is run for the base year. This step also reveals the expected agricultural income (π), needed for calibration of the household consumption decision.

4.3.2 Calibrating consumption decision

The calibration of the supply side of the farm household decision reveals the missing implicit costs, and thus the full farm-household income needed to estimate the parameters of the LES function and hence calibrate the household consumption decision.

To estimate the parameters of the LES function for the sampled farm households, we use the HPD method, with prior information on income elasticities and on the Frisch parameter from literature (Seale et al., 2003).

The HPD method is applied to the LES based on the following set of assumptions.

- In each region, the HPD model minimizes the weighted sum of normalized squared deviations of estimated regional income elasticities, farm-household uncompressible consumption, farm-household type marginal budget share, and farm-specific error terms from their respective prior, subject to a set of data consistency (FOC) constraints.
- The normalized squared deviations of farm-household uncompressible consumption and farm-specific error terms are weighted with the proportion of the farm household in the region, w_h.
- Prior information on farm-household type marginal budget share, $\bar{\delta}_{ftc,j}$, is set to the observed farm-household budget share.
- Prior information on farm-household uncompressible consumption, $\bar{\upsilon}_{h,j}$, is defined as follows: $\bar{\upsilon}_{h,j} = c^0_{h,j}\left(1+\bar{\varepsilon}^{in}_j / \theta\right)$, where c^0 is the observed consumption, $\bar{\varepsilon}_{r,j}$, is the average income elasticities and θ is the Frisch parameters taken from literature.

([7]) Note that this specification implies that farms may not necessarily calibrate to the exogenous regional elasticity but allows for farm supply responses to deviate from the regional average to guarantee farm-level heterogeneity.

$$Min\ HPD_r = \left[\sum_{h,j} \frac{(\varepsilon_{r,j}^{in} - \bar{\varepsilon}_j^{in})^2}{\sigma_j^{\varepsilon^{in}}} + \sum_{h,j} w_h \frac{(\upsilon_{h,j} - \bar{\upsilon}_{h,j})^2}{(\sigma_{h,j}^{\upsilon})^2} + \sum_{ftc,j} \frac{(\delta_{ftc,j} - \bar{\delta}_{ftc,j})^2}{(\sigma_{ftc,j}^{\delta})^2} + \sum_{h,j} w_h \frac{(e_{h,t}^c)^2}{(\sigma_{h,j}^c)^2} \right] \quad (34)$$

$$c_{h,j}^0\ p_{h,j}^0 = \delta_{h,j}(Y_h^0 - \sum_{j'} \upsilon_{h,j'} p_{h,j'}^0) + \upsilon_{h,j} p_{h,j}^0 + e_{h,j}^c \quad (35)$$

$$\sum_j \delta_{ftc,j} = 1 \quad (36)$$

$$\upsilon_{h,j} \le c_{h,j}^0 \quad (37)$$

$$0 \le \delta_{h,j} \le 1 \quad (38)$$

$$\upsilon_{h,j} \ge 0 \quad (39)$$

$$\varepsilon_{r,j}^{in} = \frac{\sum_{ftc} w_{ft} p_{fct,j}^0 c_{ftc,j}^0 \varepsilon_{ftc,j}^{in}}{\sum_{ftc} w_{ftc} p_{ftc,j}^0 c_{ftc,j}^0} \quad (40)$$

$$\delta_{ftc,j} = \varepsilon_{ftc,j}^{in} \frac{p_{ftc,j}^0 c_{ftc,j}^0}{Y_{ftc,j}^0} \quad (41)$$

$$\delta_{h,j} = \sum_{ftc} n_{ftc,h} \delta_{ftc,j} \quad (42)$$

where indices *h* denotes farm households, *ftc* farm-household type (consumption-based), *r* region and *j, j'* consumed goods (food and non-food); p^0 is the observed prices of goods; c^0 is the observed consumed quantity of goods; Y^0 is the observed 'full' farm household income; υ is the uncompressible consumption (interpreted as minimum subsistence or 'committed' quantities below which consumption cannot fall); δ is the marginal budget share ($\partial pc/\partial Y$); *n* is a parameter linking the households to their farm-household types (n equals 1 or 0); $\varepsilon_{ftc,j}$ and $\varepsilon_{r,j}$ are the estimated income elasticities per farm-household type and region, respectively.

The equations (34) and (38) represent the LES. Equations (39) and (40) compute income elasticities at regional level and the farm-household type marginal budget share, respectively. Equation (41) calculates the farm-household marginal budget share.

The estimated parameters in equations ((34) to (38)) guarantee reproduction of the actually observed consumption levels for each good (c^0) when the model (equations (2) and (15)) is run for the base year.

4.4 Food Security and Poverty indicators

FSSIM-Dev is able to compute a set of food indicators, at both individual and household levels ([8]). These indicators partially reflect one of the four dimensions of food security (availability, accessibility, utilization and stability) and can be primarily a source of information on the quality/utilization aspect of food security.

Because the LSMS-ISA survey provides food data only at household level, we have adopted the commonly used approach based on adult male equivalent (AME) to compute nutritional indicators at individual level. This

([8]) The authors would like to acknowledge valuable contributions by Thomas Allen in this section.

approach assumes that food is allocated within households according to the members' proportional energy requirements relative to an adult male (Coates, et al., 2017). Despite its wide use, one must be aware of its assumptions and limitations, mainly when measuring nutritional status for key nutritionally vulnerable groups such as women of child-bearing age, infants under 2 years of age, and children in certain contexts.

4.4.1 Food, energy and nutrient intakes

Energy intake: food consumption, expressed in kilocalories (kcal) per person per day, is a key variable for measuring and evaluating the local and global food situation.

Total energy intake, expressed in kcal per person per day, was calculated in FSSIM-Dev by summing energy intakes from different food groups κ (9) within the basket κ *j*. $c_{h,j}$ is the household consumption (in 100 g) of food *j* belonging to food group κ consumed during the last seven days; $kcal_j$ is the energy intake associated with 100 g of food *j*; and hz_h is the household size expressed in AME.

$$Ener_{h,\kappa} = \sum_j (c_{h,j,\kappa} kcal_j / hz_h) / 360 \qquad (43)$$

$$Ener_h = \sum_\kappa Ener_{h,\kappa}$$

Nutrient intakes are an important aspect of nutrition. Nutrients consist of various chemical substances in the food that makes up each person's diet. Many nutrients are essential for life, and an adequate amount of nutrients in the diet is needed for providing energy, building and maintaining the body. There are four major classes of nutrients found in food: macronutrients such as carbohydrates, proteins, lipids (fats and oils) and fibre; vitamins; minerals; and water. Macronutrients, and particularly proteins and lipids, display interesting trends for food security analyses.

- *Protein*: Protein intake, expressed in grams (g) per person per day. $prot_j$ is the protein intake associated with 100 g of food *j.*

$$prot_{h,\kappa} = \sum_j (c_{h,j,\kappa} prot_j / hz_h) / 360 \qquad (44)$$

$$prot_h = \sum_\kappa prot_{h,\kappa}$$

- *Lipid*: Lipid intake, expressed in grams (g) per person per day. lip_j is the lipid intake associated with 100 g of food *j.*

$$Lip_{h,\kappa} = \sum_j (c_{h,j,\kappa} lip_j / hz_h) / 360 \qquad (45)$$

$$Lip_h = \sum_\kappa Lip_{h,\kappa}$$

In addition to energy and nutrient intakes, a set of indicators are also computed.

- *Average food consumption of major food groups*: average intake of major food groups, expressed in grams (g) per person per day.

$$Ac_{h,\kappa} = c_{h,\kappa} / c_h \qquad (46)$$

(9) We have considered the 12 food groups proposed by FANTA (Swindale and Bilinsky, 2006): (1) Cereals, (2) Roots and tubers, (3) Vegetables, (4) Fruits, (5) Meat, poultry, offal, (6) Eggs, (7) Fish and seafood, (8) Pulses/legumes/nuts, (9) Milk and milk products, (10) Oils/fats, (11) Sugar/ honey and (12) Miscellaneous.

- *Percentage of energy intake provided by the major food groups*: share of energy provided by each food group in the total energy intake.

$$Pe_{h,\kappa} = Ener_{h,\kappa} / Ener_h \tag{47}$$

- *Percentage of energy from protein*: share of energy provided by protein in the total energy intake.

$$Pp_h = (prot_h \times 0.004) / Ener_h \tag{48}$$

- *Percentage of energy from lipid*: share of energy provided by lipid in the total energy intake.

$$Pl_h = (lip_h \times 0.009) / Ener_h \tag{49}$$

The increase in quantity and quality of fats consumed in the diet is also an important feature of diets. Two other indicators can thus be proposed.

- *Percentage protein from animal origin:* share of protein provided by foods of animal origin in the total protein intake.

- *Percentage lipid from animal origin:* share of lipid provided by foods of animal origin in the total lipid intake.

4.4.2 Poverty gap

The poverty gap (*PG*) is measured by the percentage deviation between the extreme poverty line (*pl*) of USD 1.90 equivalent per person per day, and the income for farm-household individuals (*hi*).

$$PG_{hi} = \sup\left[0, \frac{pl - R_{hi}}{pl} \times 100\right] \tag{50}$$

Income for farm-household individual (R_{hi}) is calculated as the ratio between the farm-household income (R_h) and the household size (hz_h) expressed in adult male equivalent.

The poverty gap index (*PGI*) sums the extent to which individuals on average fall below the poverty line, and expresses it as a percentage of the poverty line.

$$PGI = \frac{1}{N} \sum_{hi=1}^{N} PG_{hi} \tag{51}$$

where *N* is the total population and *PG* is the poverty gap for poor individuals.

5 The FSSIM-Dev database

This section provides a brief description of the data needed to construct FSSIM-Dev, as well as the methods and procedures employed to analyse and treat the data.

FSSIM-Dev is being applied to five SSA countries: Côte d'Ivoire, Niger, Tanzania, Senegal and Ethiopia. These countries have several differences in terms of natural conditions, resources, population size, character of the agricultural sector, crop mix, market integration, income levels (and hence poverty levels), and other socio-economic and political factors.

To generate results that are comparable across countries, a key prerequisite is the availability of data that are broadly comparable across countries. Therefore, in this report we focus only on countries where data from the World Bank LSMS-ISA are available and usable for the modelling exercise. These countries are Ethiopia, Niger and Tanzania.

As explained above, given the large heterogeneity across farm households in SSA, and the detailed information provided by the LSMS-ISA database, we opt for modelling operating at the level of the individual farm. This means that all farm households represented in the LSMS-ISA sample are individually modelled.

Before using the LSMS-ISA data, several steps were performed to screen the data and to convert them into a format compatible with the FSSIM-Dev modelling framework. This activity included, in particular, adjusting the data to FSSIM-Dev model needs, identifying and correcting out-of-range values and outliers, handling missing values, and addressing the issue of variables not available in LSMS-ISA. Variables such as quantity of labour and inputs used, consumption, and prices were treated for outliers and missing values, using Tukey's method based on Interquartile Range or winsorizing.

Four types of data are required for running the FSSIM-Dev model: fixed inputs, output and variable input data for production activities, household data, and calibration data.

(i) **Farm fixed inputs**: available farmland (i.e. total utilized agricultural area, arable land, grassland and irrigable land), per plot and at farm household–level, as well as family labour availability per season and per work activity. These data are extracted directly from LSMS-ISA and used to set upper bounds for resource constraints in the model. Data on energy, water and capital resources are not included, since they are not explicitly modelled but are captured by the behavioural function (i.e. PMP terms).

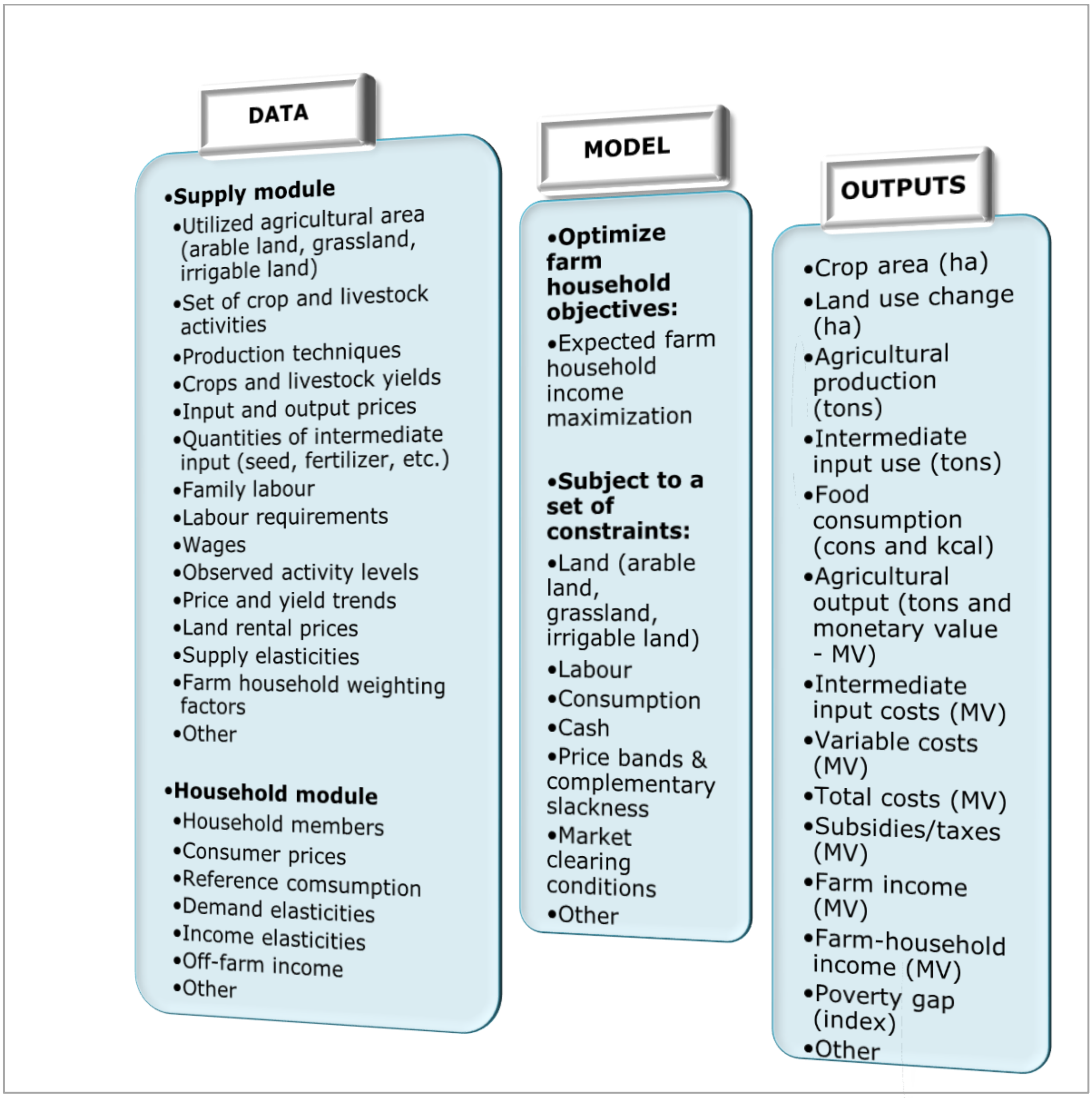
(ii) **Agricultural activities and their output and variable input data**: yields, product prices, labour requirements and accounting unit costs, for each crop and each plot. These data are used to calculate the expected gross margin per hectare, for each production activity to be embedded in the model objective function. They are also used to define input coefficients for resource and policy constraints. Most of these data are derived from the LSMS-ISA database.

(iii) **Household data** consist of data on household characteristics, livelihood activities and food and non-food expenses. Data on food consumption are collected in LSMS-ISA using a seven-day recall methodology, and are converted at season-level to be compatible with the FSSIM-Dev structure. These data also include all non-farm activities, as well as any source of income, for any member of the household.

(iv) **Calibration data** consist of observed activity levels (in hectares or head), observed quantity of goods consumed, supply elasticities and income elasticities. The observed activity level is used to calibrate the supply side of the model, assuming optimal level in the base year. The observed quantity of goods consumed is used to calibrate the consumption side of the model, assuming optimal quantity in the base year. The rest of the data (i.e. supply elasticities and income elasticities) are used as prior information. Section 4 describes in detail how these data are used in the calibration process.

Overall, most of the data required for the FSSIM-Dev model come directly or indirectly from LSMS-ISA, with the exception of some data used as prior information for model calibration. For example, most of the calibration and farm resource data are recorded in the LSMS-ISA database, and are therefore used directly in the modelling exercise. However, other data – such as prices and yields – are not directly reported in LSMS-ISA, and are therefore derived from the original LSMS-ISA variables using simple assumptions. For example, prices are approximated by dividing the values of sales by the quantity sold, and crop yields are approximated by dividing production by area. Out-of-range (negative values, outliers) or zero values for prices and yields are not suitable for use in the modelling exercise, because they are key factors in determining farmer decisions.

Figure 2. FSSIM-Dev model description



6 Selected results from application of FSSIM-Dev in sub-Saharan Africa

6.1 Ethiopia: Impact of Agricultural Commercialization Cluster Initiative

6.1.1 Context and scenario narratives

The Ethiopian economy remains dominated by agriculture: agriculture accounts for about 34% of GDP and 68% of employment (World Bank, 2018). At the same time, crop production makes up about 70% of total agricultural GDP, while over 90% of farmers are smallholders cultivating one hectare or less of land. Hence, in the Growth and Transformation Plan II (GTP II, 2015-2020) it is recognized that 'agriculture will remain the main driver of the rapid and inclusive economic growth and development … [and] main source of growth for the modern productive sectors' (National Planning Commission, 2016, Volume I, p. 78).

Louhichi et al. (2019) assess the economic implications of scaling up the performance of the Agricultural Commercialization Cluster (ACC) *woredas* to the whole respective regions of Ethiopia, using the farm-level FSSIM-Dev model. The ACC Initiative was introduced during GTP I (2010-2015) as a mechanism to integrate the Agricultural Transformation Agenda interventions along specific value chains for a limited number of priority (high-value) commodities, in high-potential areas (geographic clusters) across the four major agricultural regions: Amhara, Oromia, SNNP and Tigray. **The initiative is basically to expand the quantity and quality of three interrelated agricultural inputs** (chemical fertilizer, improved seeds, and extension and advisory services), and to **facilitate market linkages** on the output side of farming activity.

The application of FSSIM-Dev for Ethiopia is based on exploitation of the dataset of farm households resulting from the 2013/14 Ethiopia Socioeconomic Survey (ESS, wave two). This very comprehensive survey is conducted by the Central Statistics Agency of Ethiopia (CSA) in collaboration with the World Bank Living Standards Measurement Study (LSMS) team, as part of the Integrated Surveys on Agriculture (ISA) programme. Thus, the ESS 2013/14 survey is also referred to as the LSMS-ISA 2013/14 survey. ESS is a nationally representative survey of 5,262 households living in rural and urban areas. It is integrated with the Annual Agricultural Sample Survey (AgSS), and the rural households included in the ESS are a sub-sample of the AgSS sample households.

We used the 2013/14 survey because the more recent 2015/16 survey is characterized by non-typical weather conditions in several zones of the country. Since it is not desirable to calibrate the model on a non-typical base year, the previous survey round was used instead. We use survey data on 3,323 rural households in our model. Selected key sample characteristics are presented in Table 3, including for the main agricultural regions of Ethiopia. The average farm size in our Ethiopian sample is 1.22 ha; however, there is considerable variability across households and regions. In particular, farm size is especially heterogeneous in Tigray and least heterogeneous in Amhara: the coefficient of variation (i.e. the ratio of standard deviation to the mean) is 3.17 for Tigray but only 0.80 for Amhara, while for the entire country this variability indicator is 1.89. About 60% of households in our sample have a farm size of strictly less than 1 ha.

It also follows from Table 3 that rural farm households cultivate, on average, 10.3 fields with an average field size of 0.12 ha. The highest number of fields, 12.8 fields on average, is cultivated by farmers in SNNP, but their average field size is very low – 0.07 ha. On the other hand, farmers in Tigray cultivate only 6.9 fields on average, but their average field size of 0.24 ha is the largest in the country. All these sample characteristics discussed are consistent with the general view that average farm size in Ethiopia is very low, while the growing rural population has led to a further shrinking of land size and smaller plots. Fallow land made up 10.2% of the total crop area in the sample (3,539.2 ha), but at the regional level the size of fallow area ranged from 3.6% in Tigray to 17.0% in SNNP.

The large majority (86.5%) of the sample cultivated area is planted with field crops (cereals, pulses and oilseeds), most of it cereals. Sorghum makes up 20.1% of all the sample cultivated land, followed by teff (17.4%), maize (14.4%), wheat (8.3%) and barley (5.1%). However, there is a notable difference in land use by region in our sample data: teff is cultivated on the largest land areas in Amhara (22.7%), Oromia (21.8%) and SNNP (18.3%), while sorghum dominates the cultivated land area in Tigray (46.1%) and other regions of Ethiopia (34.6%). When applying the ESS sample weights to individual farmers to obtain population data, the composition of the main crops changes slightly. In particular, in the population data the shares of cultivated area for the main crops teff, maize and wheat increase, while the importance of sorghum cultivated area is largely diminished (from 20.1% to 12.9%). The population shares for cultivated area by crop then become fully consistent with the respective shares from the larger AgSS sample, confirming that the ESS sample is a representative sub-sample of the AgSS from this perspective.[10]

Table 3: Selected ESS sample characteristics

	Amhara	Oromia	SNNP	Tigray	Other regions	**Ethiopia**
Number of surveyed farm households	618	572	850	295	566	**2,901**
Total crop area, including fallow land (ha)	761.5	1,049.5	722.2	492.9	513.1	**3,539.2**
Total cultivated land area (ha)	713.5	934.2	599.6	475.3	456.2	**3,178.8**
Total production value (thousand ETB)	6,063	6,566	4,047	3,279	4,211	**24,166**
Average farm size (ha, including fallow)	1.23	1.83	0.85	1.67	0.91	**1.22**
Standard deviation of farm size (ha)	0.99	2.77	1.01	5.29	1.21	**2.30**
Average number of fields per household	9.5	11.9	12.8	6.9	7.4	**10.3**
Average field size (ha)	0.13	0.15	0.07	0.24	0.12	**0.12**
	Land use (Meher season, % of total cultivated land by region)					
Sorghum	17.49	8.39	10.03	46.08	34.61	**20.14**
Teff	22.71	21.76	18.26	12.89	3.76	**17.40**
Maize	10.59	16.95	17.69	4.48	20.93	**14.37**
Wheat	9.05	11.89	9.69	6.24	0.13	**8.30**
Barley	8.46	6.23	3.48	4.68	0.05	**5.10**
Coffee	0.21	7.46	7.67	0.00	5.80	**4.52**
Millet	7.06	1.86	0.30	8.34	4.62	**4.10**
Sesame	2.90	1.01	0.29	9.39	5.09	**3.14**
Horse beans	4.59	2.75	4.88	1.07	0.01	**2.92**
Haricot beans	1.62	4.04	3.35	0.19	2.24	**2.53**
Nuegs	2.64	5.23	0.00	0.41	0.56	**2.27**
Chat	0.25	2.18	1.83	0.17	7.72	**2.18**
Enset	0.00	1.07	8.59	0.00	0.17	**1.96**
Field peas	2.21	1.38	3.72	0.42	0.00	**1.67**
Other vegetables	0.69	1.07	4.92	0.10	1.50	**1.62**
Other pulses	2.04	0.76	0.05	0.76	3.67	**1.33**
Other oilseeds	0.68	0.66	0.13	0.08	5.72	**1.20**
Chickpeas	1.49	1.35	0.10	0.88	0.29	**0.92**
Other crops	0.57	0.89	1.04	1.71	0.02	**0.84**
Other spices	0.94	0.90	1.13	0.15	0.67	**0.81**
Other fruits	0.13	0.24	0.98	0.75	1.62	**0.63**
Lentils	1.41	0.66	0.07	0.66	0.00	**0.62**
Linseeds	1.05	0.42	0.02	0.39	0.09	**0.43**
Other cash crops	0.43	0.22	0.47	0.14	0.26	**0.31**
Potatoes	0.68	0.25	0.31	0.01	0.02	**0.29**
Banana	0.03	0.22	0.92	0.02	0.25	**0.28**
Onion	0.08	0.16	0.08	0.00	0.20	**0.11**
All crops	100.00	100.00	100.00	100.00	100.00	**100.00**

Source: ESS 2013/2014.

The ACC clusters are intended to play the role of Centres of Excellence, and to serve as 'models for learning' in the process of implementing the ACC strategy and scaling up best practices across the country. In particular, Louhichi et al. (2019) examine the effect of an increase in yields, equivalent in size to the yield improvements achieved within the ACC areas during the 2016/17 planting season (Table 4). The underlying assumption is that all farmers in the ACC-covered regions are able to perform as well as the cluster farmers in their respective regions. It is important to impose region- and crop-specific exogenous yield shocks, because it is expected that they reflect, to a certain degree, the real possibilities of smallholder farmers having to deal with differences in local climate, soil quality, infrastructure availability, marketing conditions, etc. The exercise is also in line with the GTP II strategy, where it is indicated that one of the tracks to achieving the envisaged

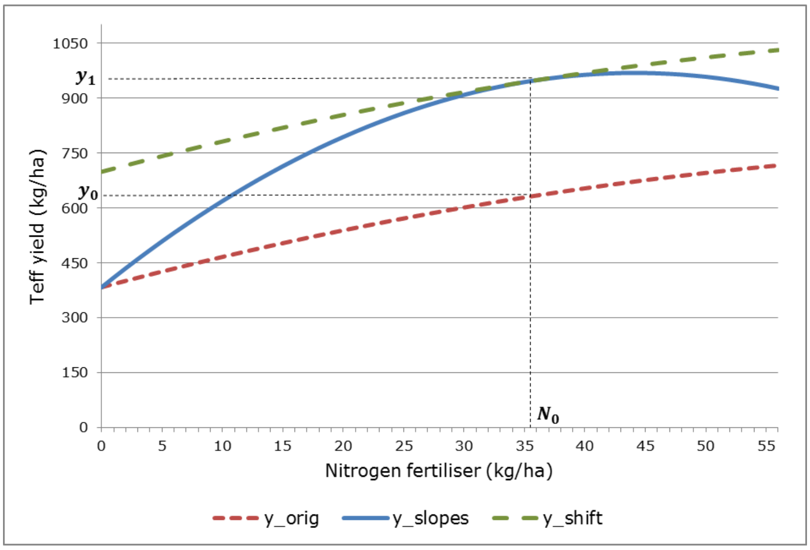
([10]) For further details of our data (production, consumption, sales, yields, conventional/improved seeds use, fertilizer use, off-farm income, sale/purchase prices, farm-household typology), see Louhichi et al. (2019). Furthermore, CSA and World Bank (2015) provides full details of the sample selection procedure and the detailed features of the ESS survey dataset.

shifts in crop productivities is ‘to raise the productivity level of the majority of farmers to the productivity level attained by model farmers’ (National Planning Commission, 2016, p. 121).

Table 4: Yield changes (%) included in simulation scenarios

	Amhara	Oromia	SNNP	Tigray
Maize	49.78	18.39		
Wheat	41.35	28.16	62.54	54.86
Teff	34.79	21.14		39.78
Barley	10.70	24.69		
Haricot beans			5.20	

Figure 2: Teff yield to fertilizer use response functions, before and after an exogenous 50% increase in yield



NB: The original, with increase in slopes only, and with increase in intercept only fertilizer response functions are denoted, respectively, by y_orig, y_slopes and y_shift.

From a theoretical point of view, the ACC initiative should lead to higher yield productivities (for details, see Louhichi et al., 2019). However, in the face of limited available information, we considered two 'extreme' cases of possible change in the yield response functions: Shift vs Slope scenarios. Adding seed type distinctions, the following four scenarios were assessed.

1. **Shift_AllSeeds**: moving up the yield curves parallel to the original ones, for all farms in the four regions and all seed types.
2. **Shift_ConvSeed**: moving up the yield curves parallel to the original ones, for all farms in the four regions but only for conventional seeds.
3. **Slope_AllSeeds**: moving up the yield curves by changing their slopes, for all farms in the four regions and all seed types.
4. **Slope_ConvSeed**: moving up the yield curves by changing their slopes, for all farms in the four regions but only for conventional seeds.

All the shocks imposed correspond to the 2016/17 region- and crop-specific productivity changes as summarized in Table 4. As an illustration of the Shift and Slope cases, consider the fertilizer response function for teff of the form $y = 383.03 + 8.781N - 0.0507N^2$, where y is yield in kg/ha and N is applied nitrogen fertilizer in kg/ha. A 50% increase in teff yield would result in new fertilizer response functions, corresponding to the Shift and Slope cases, as illustrated in Figure 2. Note that the optimal fertilizer use is restricted to exactly equal to its observed level as applied by the farmer. Notice also that the slopes of the fertilizer response function corresponding to the case where only the slope coefficients have been shocked are always higher (in absolute value) for all non-optimal quantities of fertilizer use, compared with those where only the shift parameter has been changed. This implies that, in the first case, there will be a lower reaction in terms of fertilizer use by a rational farmer in response to a given change in fertilizer cost and/or teff output price.

6.1.2 Main results

Below, we briefly discuss a few selected results of the impact evaluation for upscaling ACC. Table 5 shows the country-wide production impacts under the four ACC scenarios, and their decomposition into productivity vs area effects. Across all ACC scenarios considered, the average country-level production increases for wheat, teff, maize and barley were found to be 29.6%, 21.1%, 12.8% and 12.6%, respectively. Importantly, production increase is driven by rise in land productivity, rather than area expansion (through bringing fallow land into cultivation) and/or area reallocation. The only 'notable' exception is maize, where on average across all ACC scenarios, about 5% of production increase is explained by area expansion/reallocation.

Table 5: Production change and its yield/area decomposition

	Shift_AllSeeds	Shift_ConvSeed	Slope_AllSeeds	Slope_ConvSeed	Average across all scenarios
	Production change (% of baseline production)				
Teff	24.79	24.10	18.09	17.44	21.10
Wheat	34.36	31.01	28.03	24.81	29.55
Maize	24.22	8.45	16.49	2.22	12.84
Barley	16.59	16.16	8.81	8.65	12.55
Sorghum	-0.15	-0.13	-0.04	-0.02	-0.09
Millet	0.00	0.00	0.00	0.00	0.00
Pulses	-0.01	0.05	-0.03	0.03	0.01
Oilseeds	-0.17	-0.07	-0.09	0.00	-0.08
Root crops	-0.01	-0.01	0.00	0.00	-0.01
Fruit crops	-0.06	-0.02	-0.05	-0.01	-0.03
Chat	-0.45	-0.38	-0.22	-0.17	-0.30
Coffee	-0.19	-0.19	-0.15	-0.15	-0.17
Enset	-0.05	-0.03	-0.01	-0.01	-0.02
Other crops	-0.14	-0.12	-0.02	0.00	-0.07
	Productivity effect (% of Production change expressed in physical unit)				
Teff	99.57	99.56	99.82	99.82	99.69
Wheat	99.45	99.41	99.78	99.77	99.60
Maize	96.31	94.10	97.06	92.96	95.11
Barley	101.03	101.09	100.17	100.22	100.63
	Area effect (% of Production change expressed in physical unit)				
Teff	0.43	0.44	0.18	0.18	0.31
Wheat	0.55	0.59	0.22	0.23	0.40
Maize	3.69	5.90	2.94	7.04	4.89
Barley	-1.03	-1.09	-0.17	-0.22	-0.63

Source: model results

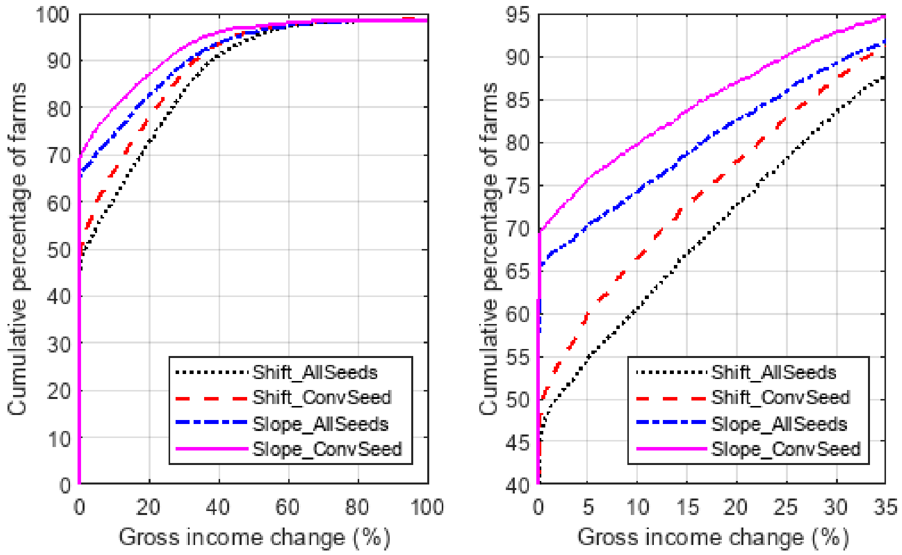
The gross income impacts at the country and regional level are presented in Table 6. It is found that scaling up of the ACC policies to the respective regional level would increase income at the country level by between 10.2% and 18.9%, depending on the scenarios considered. Average gross income increase across all scenarios is estimated at about 14%. Regions most positively affected are Amhara and Oromia, namely because in these regions improved productivity shocks were implemented for all four targeted cereals (Table 4).

Table 6: Gross income change (% change relative to the baseline)

	Shift_AllSeeds	Shift_ConvSeed	Slope_AllSeeds	Slope_ConvSeed	Average across all scenarios
Ethiopia	18.90	14.68	14.12	10.23	14.48
Amhara	22.71	15.42	15.20	8.08	15.35
Oromia	20.40	17.40	15.94	13.47	16.80
SNNP	8.85	6.36	8.03	5.62	7.22
Tigray	14.92	12.26	12.57	10.00	12.44

Source: model results

Figure 3: Distribution of farm-level gross income change (% of the baseline)



(a) All farms (b) Affected farms

Figure 3 shows the distribution of gross income change across individual farms (the second panel zooms in to more vividly show the differences between the four scenarios for the affected farms). For a given cumulative share of farms, the following relation is observed in terms of changes in gross income: the lowest income change is observed under the Slope_ConvSeed scenario, followed by Slope_AllSeeds, then Shift_ConvSeed and finally Shift_AllSeeds. For example, 85% of farms experience an increase in their gross income of up to 16.9%, 23.8%, 27.4% and 31.7% under the Slope_ConvSeed, Slope_AllSeeds, Shift_ConvSeed and Shift_AllSeeds scenarios, respectively. This is an expected outcome, since under for example the Shift_AllSeeds scenario, all farmers irrespective of seed type used are assumed to experience an exogenous productivity improvement. These distributional findings also explain the aggregate income impacts under the different scenarios shown in Table 6.

The estimated changes in gross income by farm type are shown in Table 7. The largest income change is experienced by farms specializing in field crops, which is not surprising as the ACC targeted crops considered are field crops. Farm households specializing in permanent crops gain a small increase in income of roughly 1.1% on average. In terms of economic size, the largest increase in gross income is experienced by medium-large farms (i.e. farms with total production value of over ETB 9,000). The average income gains across all scenarios are found to be 12.4%, 8.9% and 5.9% for, respectively, medium-large farms, small farms and subsistence farms. The heterogeneity of income change across different economic sizes is not surprising either, given that the increase in land productivity under ACC interventions is higher in medium-large farms than in small farms.

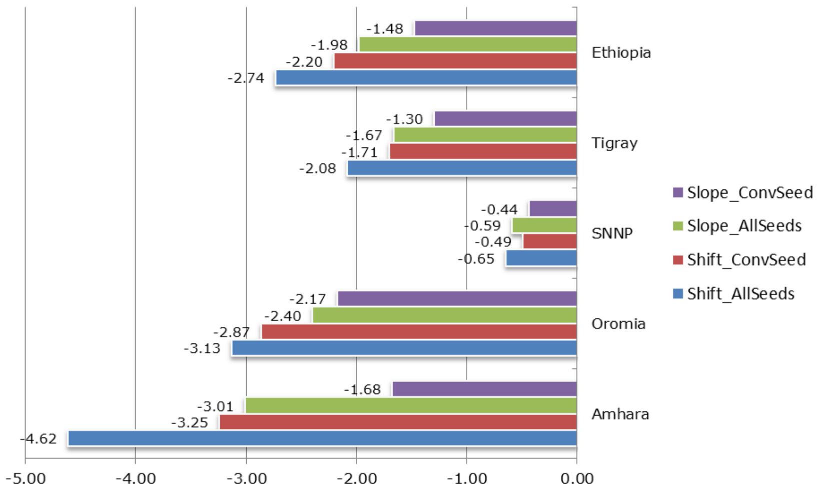
Table 7: Gross income change by farm type (% change relative to the baseline)

	Shift_AllSeeds	Shift_ConvSeed	Slope_AllSeeds	Slope_ConvSeed	Average across all scenarios
	Farm specialization				
Field crops	17.99	14.72	13.12	10.10	13.98
Permanent crops	1.44	1.11	1.00	0.68	1.06
Mixed	10.17	6.63	7.32	3.92	7.01
	Economic size				
ES1 (<ETB 4000)	7.87	6.55	5.13	3.88	5.86
ES2 (ETB 4000-9000)	12.70	9.57	8.13	5.19	8.90
ES3 (>ETB 9000)	15.74	12.68	12.05	9.22	12.42
	Farm specialization and economic size				
Field & ES1	11.48	9.37	7.49	5.43	8.44
Field & ES2	16.94	12.86	10.87	7.02	11.92
Field & ES3	19.45	16.28	14.89	12.03	15.66
Permanent & ES1	0.99	0.70	0.83	0.56	0.77
Permanent & ES2	1.43	1.08	0.85	0.50	0.96
Permanent & ES3	1.57	1.24	1.10	0.77	1.17
Mixed & ES1	6.86	6.06	4.33	3.67	5.23
Mixed & ES2	7.46	5.34	4.75	2.81	5.09
Mixed & ES3	14.17	7.95	11.02	4.90	9.51

Source: model results

As expected, the extreme poverty gap[11] decreases through scaling up the ACC policies: on average across all four scenarios considered, the extreme poverty gap is assessed to decrease by about 2.1% throughout the country, while the corresponding region-specific average poverty effects in Amhara, Oromia, SNNP and Tigray are found to be, respectively, -3.1%, -2.6%, -0.5% and -1.7% (see Figure 4).

Figure 4: Change in extreme poverty (% change relative to the baseline)



6.2 Niger: Impact of small irrigation programme

6.2.1 Context and scenario narratives

The FSSIM-Dev model has also been used to perform an *ex ante* assessment of an emblematic agricultural policy of the Republic of Niger: the *Stratégie de la Petite Irrigation au Niger* (SPIN) programme for the development of small irrigation. This application of the FSSIM-Dev model in Niger is based on the LSMS-ISA 2011 survey. This very comprehensive survey was conducted by the *Institut National de la Statistique* (INS) of

(11) The extreme poverty gap is measured as the difference between farm household income per household unit and the extreme poverty line of USD 1.90 equivalent per person per day (ETB 55).

Niger with the support of the World Bank LSMS group. The data were collected in two waves, to cover both dry season (December 2010 to May 2011) and rainfed season (June 2011 to November 2011). The full sample of the survey includes about 4,070 households, all involved in agricultural activities (including livestock). The survey sample was designed using two-stage stratified random sampling, and the final sample is representative at the national and regional levels for both urban and rural areas.

Table 8 presents the main characteristics of the farms included in the LSMS-ISA 2011 survey in Niger. The entire sample of households in this survey is larger, but for the purposes of this case study (as mentioned above), only a share of this sample was used as we focused here on households engaged in cultivation of land. About 1,750 households who only perform livestock breeding activities were thus removed, leaving the sample of farms that is used for this modelling exercise on small irrigation. Among the farms included in our final sample, the mean cultivated area is about 4.99 ha, with a maximum of 6.54 ha observed in the Tillabéry region and a minimum of 1.5 ha in Agadez. Table 8 also gives some indication of the type of crop specialization observed in Niger, for both the dry and the rainy season. Millet, cowpea and sorghum are by far the majority crops cultivated in the rainy season (the *hivernage* season) in most of the country; only the northern and driest region of Agadez does not display this pattern. Overall, millet occupies almost half the total cultivated land in Niger in the rainy season, and together with sorghum and cowpea this proportion goes up to almost 90% of the total. Land allocation in the dry season shows more variability across regions. Some regions are clearly specialized in one or a few crops, such as Diffa with sweet pepper (red and green), or Agadez and Tahoua with onions.

Table 8. Main features of farms in the LSMS-ISA 2011 sample for Niger

	Agadez	Diffa	Dosso	Maradi	Tahoua	Tillabéri	Zinder	Niamey	Niger
Number of farms in the sample	108	227	389	389	378	374	384	73	**2322**
Mean cultivated area in rainy season (ha)	0.97	4.48	4.76	5.0	4.03	7.76	5.39	1.94	**4.99**
Standard deviation	1.5	3.66	3.59	4.99	3.87	6.54	5.39	1.94	**4.94**
Number of irrigated farms in the sample	89	53	37	7	54	41	20	46	**347**
Mean cultivated area in dry season (ha)	0.25	1.0	0.25	0.09	0.44	0.62	0.91	0.49	**0.54**
	Crop allocation in rainy season (% of total cultivated land, by region)								
Millet	18.7	57.0	46.9	38.3	43.8	57.1	39.6	64.2	**47.2**
Sorghum	13.9	15.0	7.3	22.0	23.3	10.0	20.9		**15.5**
Rice	16.4							6.0	**0.6**
Cowpea	4.4	10.1	28.3	33.1	26.4	21.6	30.7	22.9	**25.6**
Peanut		4.3	6.5		4.7				**3.6**
Onion	34.9								**0.6**
	Crop allocation in dry season (% of total cultivated land, by region)								
Rice		15.7	28.6			48.6		19.3	**16.9**
Sweet Potatoes			27.3			19.8			**5.1**
Pepper		74.8					7.8		**22.3**
Chili pepper				10.9		6.2	6.0		**2.9**
Cabbage				23.8	8.8		6.5	16.2	**5.1**
Tomato				10.1	6.3		8.3	20.1	**6.5**
Jaxatu							52.2		**8.1**
Onion	45.2			7.9	77.4	7.5			**16.5**
Squash						7.9	5.2		**2.4**

Source: Author's calculation based on LSMS-ISA 2011.

In 2018, Niger ranked last (189th out of 189 ranked countries) in the Human Development Index (HDI), which reflects countries' achievements in health, education and standard of living (UNDP, 2019). Niger's population was about 20.7 million people in 2016, and over 80% of this population lives in rural areas. Using the poverty headcount ratio at USD 1.90 per day (2011 PPP), about 44.5% of the population of Niger is regarded as poor, according to the latest estimate by the World Bank for 2014. In addition, 55.2% of the rural population was below the national poverty line in 2013 (World Bank, 2019). However, the extreme poverty rate has declined in recent decades, from 63% in 1990 to 48% in 2011 (HCi3N, 2012).

In Niger, agricultural production faces very hostile conditions, due to the arid climate regime of the country characterized by low rainfall, a short rainy season and an overall very dry and hot climate. Despite these constraints, agriculture remains the most important sector of the Nigerien economy, both socially and economically. In 2010, its contribution to GDP was estimated to be around 45% and the sector employed more than 80% of the workforce (INS, 2012). Additionally, Niger is at the forefront of the potential negative impacts of climate change. The country is particularly vulnerable to land degradation and desertification in general. It could suffer significant declines in cereal yields if farming systems are not adapted to changing climatic conditions, including the likely shortening of the rainy season.

Therefore, one of the challenges for agriculture in Niger is to better manage water supply and soil fertility, in the most sustainable way. This could be achieved through better exploitation of rainwater, and better management of irrigation systems to improve the overall efficiency of water use. In addition, irrigated agriculture would lead to improvement and stabilization in agricultural yields, which would in turn enable farming households to meet their subsistence needs and increase their income. It would also strengthen their resilience to climate change. The development of irrigation is thus an important lever for increasing agricultural production in Niger.

To support the development of its agricultural sector, in 2012 the government of Niger adopted a common framework for all rural and agricultural policies, called the 3N initiative ('Nigeriens Nourishing Nigeriens'). The main objective of this initiative is to promote domestic production of food products, in order to strengthen the country's food supply and resilience to food crises and natural disasters (HCi3N, 2012). One of the main themes of the 3N initiative is the development of small-scale irrigation, i.e. small irrigation infrastructures implemented at the level of an individual farmer or a small community of farmers, such as river pumps, wells or small hill reservoirs. This specific programme of the 3N initiative is called *Stratégie de la Petite Irrigation au Niger* (SPIN). The objective of SPIN is to secure, by 2025, an increase of 47,000 ha in the irrigated area of Niger, including (Secrétariat de la SPIN, 2019):

- 4,200 ha of new small irrigation land per year;
- 500 ha of rehabilitated area for small irrigation per year.

The FSSIM-Dev model has been used to carry out an estimation of the effects that this increase in irrigated area could have on Nigerien farm households (Tillie et al., 2019). This is an *ex ante* evaluation, i.e. it seeks to estimate these effects in advance of the full implementation of SPIN, with the aim of informing decision-makers on the expected impacts of the policy.

Two scenarios were constructed. In both cases, we simulated the increased access in irrigated land for agricultural households, and then we assessed the potential impacts in terms of crop rotation, land distribution between irrigated and rainfed crops, agricultural production, and income. The two scenarios are as follows.

- Scenario 1: The first scenario corresponds to the situation that would prevail if the objective of developing 47,000 ha of land for small-scale irrigation was achieved. Assumptions regarding financing of the investment are based on the main SPIN mechanism: 10% upfront payment by the farmer, 40% subsidy and 50% credit.
- Scenario 2: The second scenario simulates the effects of an increase of 160,000 ha in irrigated land, to reach a total of 270,000 ha, corresponding to the estimated potential for irrigation.

6.2.2 Main results

The simulation results, in terms of total cultivated land and irrigated land, are displayed in Table 9. As expected, these results are consistent with the hypothesis for the scenarios regarding the increase in irrigated land. Logically, most of the increase in irrigated area occurs during the dry season, when there is a higher need for water in agriculture. For this reason, we will mainly focus here on changes happening during this season. Table 10 shows the relative changes in crop cultivated area, disaggregated by regions, for the dry season and under the first scenario. It shows very large increases for some crops, in relative terms. In most cases, these are explained by the very small area dedicated to those crops in the baseline; this increases by only a few hundred hectares under scenario 1, but this still represents a large relative increase. For instance, onion cultivated area in dry season in Maradi was as low as 18 ha, according to the data from the baseline, but it rises to 654 ha under scenario 1 – an increase of 3,450%. Focusing on crops that were cultivated on a fairly large area in the baseline (over 1,000 ha in a given region), the most significant changes are for onion in Tahoua (+49%), tomato in Niamey (+84%), sweet pepper in Diffa (+25%) and sweet potatoes (+202%), squash (+173%) and chili (+108%) in Tillabéri.

Table 9. Changes in total cultivated area and irrigated area

	Total cultivated area in rainy season (ha)		Total cultivated area in dry season (ha)		Total cultivated area both seasons (ha)	
	Total	Irrigated	Total	Irrigated	Total	Irrigated
Baseline	10,529,461	41,772	106,609	106,609	10,636,070	148,380
Scenario 1	10,522,057	48,580	153,872	153,872	10,675,929	202,451
Scenario 2	10,527,737	96,443	273,459	273,459	10,801,196	369,901

Source: model results

Table 10. Land allocation changes, in the dry season, under scenario 1 (percentage change)

	Agadez	Diffa	Dosso	Maradi	Tahoua	Tillaberi	Zinder	Niamey	NIGER
Onion	*246.7*	*3.1*	*642.4*	*3,450.2*	49.4	0.0	*4.1*	*359.5*	54.8
Rice	-	0.6	14.9	-	-	5.3	*0.0*	7.8	5.6
Sweet Pepper	-	*25.1*	*0.0*	*91.8*	-	0.0	0.0	*-100.0*	17.7
Squash	*711.0*	*0.0*	*2,016.7*	-	*546.2*	173.5	*866.1*	*268.8*	267.7
Chili	*1,715.0*	*0.0*	*0.4*	*568.5*	-	108.0	*144.5*	*85.1*	133.2
Sweet Potato	-	-	*16.7*	*0.0*	-	202.5	-	*1,803.9*	139.1
Cassava	-	*0.0*	*0.9*	-	-	0.2	0.0	*-2.6*	0.2
Tomato	*-84.1*	*0.0*	*0.0*	*48.2*	*10.1*	*0.0*	*9.4*	100.4	35.1
Cabbage	-	*0.0*	*3,876.4*	*75.6*	*9.3*	*19.7*	*0.0*	*84.5*	251.6
Lettuce	-	*0.0*	*506.5*	*178.1*	*369.0*	*672.2*	*64.2*	*8.4*	272.1
Other crops	*156.8*	0.0	100.8	*174.9*	3.0	15.3	0.0	*63.6*	41.4

Note: Figures are in italic when the area cultivated in the baseline was lower than 1,000 ha.

Source: model results

The gross income impacts for both scenarios, at the country and regional level, are presented in Table 11. The results show the increased irrigated area having a large impact on income during the dry season. This is consistent with the idea that some farms had virtually no income during the dry season in the reference period, while with access to irrigation they are now able to engage in productive activities during that season. Over the entire year, implementation of SPIN would lead to a 12.5% increase in gross income for farms in Niger, while a further extension of irrigated land (Scenario 2) would increase this income by 71.9%.

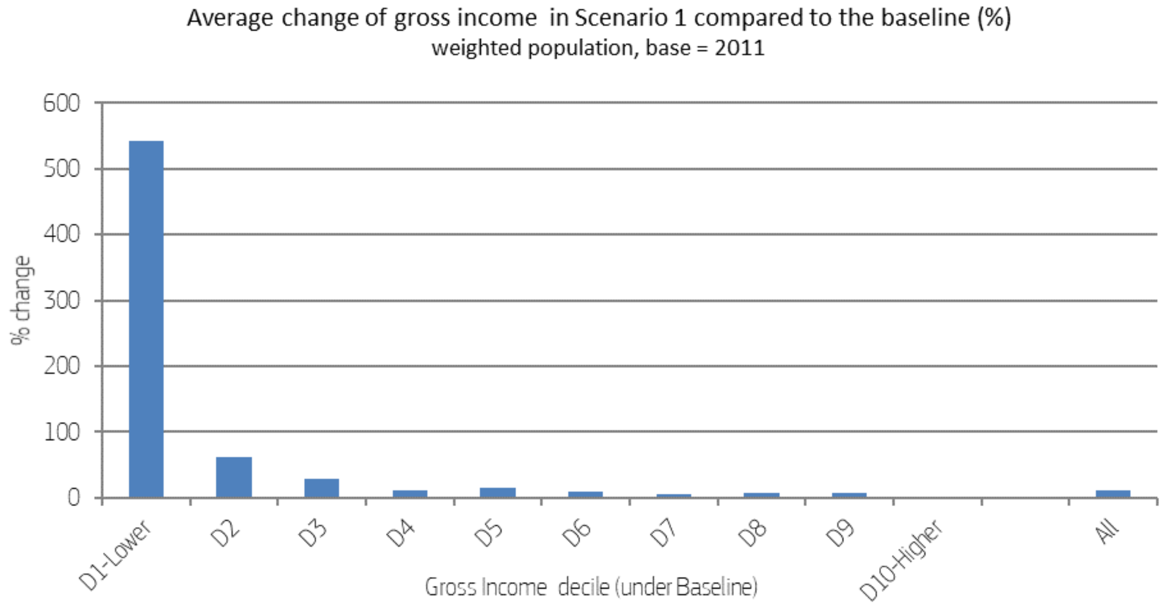
Table 11. Changes in gross income, by region (percentage change relative to the baseline)

	Agadez	Diffa	Dosso	Maradi	Tahoua	Tillaberi	Zinder	Niamey	NIGER
Changes in dry season									
Scenario 1	316.4	27.9	462.1	835.8	38.2	110.6	40.0	536.4	77.9
Scenario 2	57.2	54.3	1,382.3	35,662.4	124.9	282.6	1,570.6	267.9	422.8
Changes in entire year									
Scenario 1	64.1	14.0	18.9	2.9	17.3	12.5	1.6	329.6	12.5
Scenario 2	17.4	33.3	66.5	138.9	60.2	55.0	73.2	123.7	71.9

Source: model results

The model results can also demonstrate the potential redistributive effects of the small irrigation programme at the level of agricultural households. To show this, we classified all households in the sample by decile, according to their gross farm income in the baseline. Figure 5 shows the average increase in gross farm income induced by the implementation of Scenario 1, for each decile of farm income. It shows that this programme is helping to reduce inequalities in agricultural income: agricultural households in the poorest 10% in the baseline (annual farm income below XOF 66,000) are those who would see their income increase most through access to irrigation. Their average farm income would increase more than six-fold under Scenario 1. At the other extreme, households in the richest 10% (gross farm income above XOF 626,600) would see an increase in agricultural income of only about 1%.

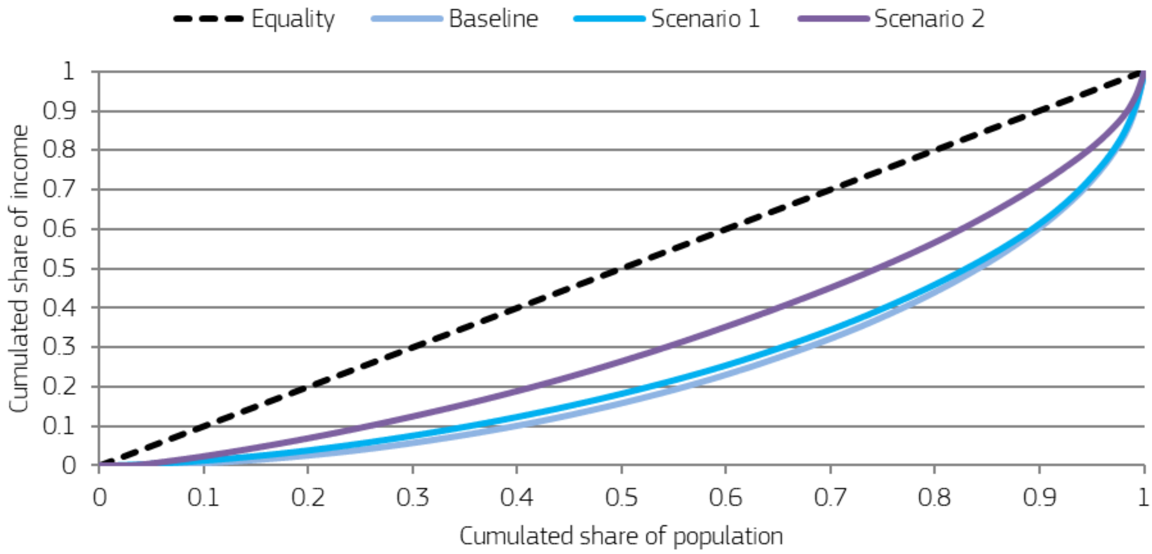
Figure 5. Effects of the Scenario 1 on agricultural income by decile



Source: model results

Finally, the model results also enable calculation of the GINI index for agricultural income distribution for all farms in Niger. The GINI index measures the level of inequality associated with income distribution in a population. A perfectly even distribution corresponds to a GINI index of 0. For the households in our sample, the GINI index for the baseline is 0.50. Implementation of a small irrigation programme such as SPIN (Scenario 1) would reduce the GINI index to 0.45 – more accurately, a decrease of 4.65 points. These results are therefore consistent with previous ones, and show that SPIN would have a positive effect on inequalities in rural Niger. Figure 6 shows the Lorenz curve for agricultural income distribution, under the baseline situation and under the SPIN simulation (Scenario 1). Under Scenario 2, the GINI index would decrease by more than 15 points to 0.34, moving towards more equal distribution of agricultural incomes among the rural population.

Figure 6. Lorenz curve for the sampled farms under the different scenarios



Source: model results

6.3 Tanzania: Impact of produce cess reform options

6.3.1 Context and scenario descriptions

Tanzania is a vast country. Excluding inland water bodies, the total surface of land in Tanzania is 88.5 million ha. The Tanzanian territory is not only vast but also rich and encompasses a large diversity of agro-ecological zones (AEZs). This wide variety is enabled firstly by the large variability in topographic conditions, with altitudes ranging from 0 to 5,895 m above sea level. This translates into a rich and complex hydrological profile, with seven watersheds in the country. The high diversity is also explained by the wide variations in rainfall (from 100/250 mm to 2,500 mm per year) and in rainfall pattern, temperature and soil conditions. Meanwhile, although Tanzania succeeded in reaching steady and strong economic growth of 7% per year over the last 15 years, agricultural productivity has remained low and the agricultural sector did not significantly benefit from the economic growth. As a result, and given the large population growth that heightens the need to increase agricultural production, the area of agricultural land has increased. While it covered 36% of the surface of the country in 2000, its share increased to 45% (39.6 million ha) by 2015, mostly at the expense of forest land (FAO, 2019).

The government has admitted that the main constraints to transformation of the agricultural sector are actually the lack of involvement of the private sector, and the current policy environment that is not encouraging farmers to produce more in order to achieve commercial activities with the production surpluses. Having identified this problem, the government decided to address one cause of it by reforming the rural fiscal system, through a reduction in the produce cess (tax). The produce cess is a turnover tax on agricultural output, charged by local government authorities (LGAs) at a given rate (percentage of the farm-gate price). This tax constitutes the major source of revenue for many LGAs, especially rural ones where on average 43% (and up to 90%) of their own revenue relies on the produce cess (Nyange et al., 2015). Despite a previous reform implemented in 2003, the cess tax is strongly criticized by agricultural stakeholders, who have expressed many concerns that it: (i) reduces the incentive to the farm to produce (and sell) more; (ii) affects farm profitability; (iii) reduces the competitiveness of Tanzanian agriculture abroad; (iv) creates market distortion, as the level of taxation is not equal between LGAs (creating tax avoidance strategy); (v) worsens food security and poverty levels; and (vi) creates uncertainty over the final producer price if there is lack of clarity over the eligibility of products (e.g. whether crops produced for seeds might be subject to the tax). In response to repeated stakeholder pressure, the government decided in 2017 to amend the Local Government Finance Act a second time, by reducing the cap of the cess rate from 5% to 3%.

The plan now is to go further by decreasing the cess rate even more in 2020, to continue reducing disparities in current rates across both crops and LGAs. Several options are currently under discussion.

- Total removal of the produce cess for all crops (NoCess scenario).
- Uniform cess rate reduction for all crops from 3% to 1% (1%Cess scenario).
- Total removal of the produce cess only for staple crops and tea. For cash crops (except tea), the produce cess remains unchanged (NoCess_stap scenario).

The application of FSSIM-Dev in Tanzania enabled evaluation of the potential impacts of these three reform options on farm household livelihoods, particularly on land use, crop mix, production, farm income and poverty gap, as well as on LGA tax revenues. All the detailed methodology and results can be found in Ricome et al. (2019). Below, we present the data used and briefly discuss a few selected results of the *ex ante* impact assessment achieved.

The data used are taken from the 2012/13 Tanzania National Panel Survey, also known as the Tanzania Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS–ISA). This is a representative survey of households living in both rural and urban areas, but with a strong focus on agriculture (see section 5). There were 5,015 households included in the 2012/13 survey, among which 3,212 were farmers. After the data cleaning process and taking out a few farm households, the model was applied to 3,134 farm households spread throughout the regions of Tanzania.

Table 12 presents some key characteristics of our farm-household sample, at both national and regional levels. The average size of the farm households in the sample is around 1.5 ha, which is slightly low but in line with the 2007/08 agricultural census (National Bureau of Statistics, 2012). We observe significant disparities between regions, with the smallest average farm size (0.87 ha) in the Western highlands and the largest (2.24 ha) in the Semi-arid and Arid zone. Also, around 75% of the farms and 80% of the cultivated lands in the sample are concentrated in three main zones: Coastal plain, Plateau/South-western highlands, and Semi-arid/Arid. The remaining three zones together represent less than 25% of the sample farms and less than 20% of the cultivated land. This indicates that some regions are more agriculture-oriented than others, so the number of farm households from these zones – and their corresponding cultivated areas – dominate in the sampling frame.

Table 12: Key sample characteristics of the FSSIM-Dev data for Tanzania

	National	Coastal plain	Northern highland	Plateau/ Southwest highland	Semi- arid/ Arid	Southern highland	Western highland
Number of households surveyed	**3,134**	943 (30.1%)	167 (5.3%)	785 (25%)	638 (20.3%)	346 (11.1%)	255 (8.2%)
Average farm size	**1.47**	1.12	1.07	1.7	2.24	1.09	0.87
Equivalent adult per household	**3.98**	3.7	4.06	4.21	4.4	3.4	3.87
Share of cultivated land over total sample cultivated land	**100**	22%	4%	29%	31%	8%	5%
	Land use in the Long rainy season (% total cultivated land in each region)						
annual crop	**85**	67	93	90	91	88	87
perennial crop	**15**	33	7	10	9	12	13
maize	**34.6**	22.9	61.6	36.9	34.9	49.6	28.6
rice	**8.5**	10.5	1.8	10.2	8.1	6.2	3.7
sorghum/millet	**4.3**	2.6	2.2	2.5	8.9	0.6	1.9
cassava	**6.6**	13.2	0.2	8.0	1.3	1.7	13.8
other roots	**3.3**	1.9	1.4	4.7	2.1	3.4	8.1
banana	**3.5**	4.6	3.7	4.6	0.7	6.0	6.0
beans	**6.9**	1.1	16.4	10.0	1.5	14.1	23.2
other legumes	**11**	10.5	3.8	10.1	15.5	6.8	6.2
cashew nut	**5.8**	18.8	0.0	1.0	4.8	0.0	0.0
cotton	**4.7**	0.0	0.0	2.9	12.2	0.0	0.2
other annual crop	**5.3**	4.2	5.9	4.6	6.8	5.8	0.8
other perennial crop	**5.5**	9.8	3.0	4.4	3.3	5.8	7.5

Source: author's own calculation from the LSMS-ISA 2012/13 survey

The Table also highlights the strong heterogeneity across regions in terms of land use. This is, however, not surprising and fully consistent with the national statistics and also other published studies (FEWS NET, 2008). For example, the Coastal plain region which has low agricultural potential, particularly for cereals, is characterized by a higher presence of perennial crops (coconut, mango, orange in the north and cashew nut in the south) and cassava in comparison to other regions, to the detriment of maize. In the Semi-arid and Arid zone, sorghum, millet and legumes are quite common in comparison to other regions, while beans remain very low due to the high risk of failure caused by the scarcity of rainfall. Conversely, in the Northern highlands, which is a mountainous zone with abundant rainfall and fertile soils, maize and beans dominate and are intercropped with cash crops such as coffee and fruit trees (banana, avocado, etc.). In the Plateau and South-western highlands, maize, cassava and beans are the main crops, along with rice (north/central part) and cassava (southern part). The Southern highlands is considered one of the most productive area of Tanzania due to the presence of fertile soils, good altitude and rains. Although several farming systems coexist in the zone, farmers prioritize maize, beans and cash crops (rice, cocoa, coffee, horticulture, etc.). Finally, in the Western highlands, the farming systems relies on the combination of banana-beans-coffee in the north, and root and tuber crops with beans and maize in the south. All these regional characteristics are well captured in the sample.

6.3.2 Main results

In the following sections, we present selected model outputs by gathering all the crops into two crop categories: staple crops and cash crops. Given the number of crops, we present the results thus for the sake of clarity, but most importantly because it is a crucial distinction made by Tanzanian policymakers.

Table 13 shows the changes in production and nitrogen use under each simulated scenario, at national level and when the farms are gathered by economic size and crop orientation. At national level, a total removal of the cess (NoCess scenario) leads to an increase in production, for both staple and cash crops, of around 5%; a reduction in cess from 3% to 1% (1%Cess scenario) raises production by only 3.5%, which is still not negligible. Furthermore, we observe that the changes are slightly bigger for staple crops. Yield response to nitrogen is, in fact, slightly higher for staple crops than for cash crops, leading to a higher use of nitrogen on the former crop type. As expected, the removal of tax for only staple crops (NoCess_stap scenario) significantly boosts their production through an increase in nitrogen use. On the other hand, the production of cash crops is reduced by 1.23%. The results show the extent to which large farms will benefit more than small ones from the reform options. This difference in impact is however not surprising, and it is explained by the fact that the volumes sold on the market are definitely not the same across farms, and thus that total savings allowed by the cess reforms are much higher for large farms than small ones. The direction and magnitude of changes are quite similar across crop specializations. This is because the cess reforms target all crops in the first two scenarios, and a large range of crops in the third one (NoCess_stap), and therefore all farm specializations are affected in some way. The exception is under the Cess_stap scenario, where farms specialized in annual cash crops seem to be much more negatively affected than the other ones. Also, it is interesting to note that, for a uniform reduction in cess rate for staple and cash crops, farms specialized in staple crops will mainly enhance staple crops (under the NoCess scenario, 5.05% increase in staple crops vs 3.03% increase in cash crops), while farms specialized in annual cash crops will mainly boost cash crops (under the NoCess scenario, 3.74% increase in staple crops vs 4.43% increase in cash crops).

Table 13: Production change under simulated scenarios, at national level and by economic size and crop specialization (percentage change relative to the baseline)

		Staple crops			Cash crops		
		No Cess	1% Cess	NoCess_stap	No Cess	1% Cess	NoCess_stap
Tanzania	Production	5	3.54	5.38	4.97	3.27	-1.23
	Nitrogen use	24.1	15.5	24.5	18.5	12	-0.69
Economic size							
Small	Production	1.30	0.85	1.39	2.26	1.34	-0.19
	Nitrogen use	11.22	7.33	11.35	21.81	14.28	-0.46
Medium	Production	4.06	2.73	4.21	4.44	3.09	-0.13
	Nitrogen use	15.98	10.33	16.00	24.13	15.85	-0.40
Large	Production	6.10	4.38	6.63	5.29	3.44	-1.62
	Nitrogen use	31.99	20.50	32.65	17.70	11.52	-0.74
Crop specialization							
Staple crops	Production	5.05	3.62	5.36	3.03	1.81	-0.68
	Nitrogen use	26.42	17.52	26.90	33.78	16.59	-7.20
Annual cash crops	Production	3.74	2.55	4.36	4.43	2.48	-2.74
	Nitrogen use	26.79	16.74	28.37	17.56	11.55	-0.39
Permanent crops	Production	6.71	4.77	7.27	3.64	2.62	-0.23
	Nitrogen use	14.08	8.96	13.99	20.15	13.60	-0.08
Mixed crops	Production	5.19	3.62	5.54	7.02	4.90	-.87
	Nitrogen use	20.69	12.57	20.54	17.45	12.26	-.20

Source: model results.

Figure 7Figure 7 presents income changes (with decomposition into staple and cash crop income) at national level, under the three simulated scenarios. The NoCess scenario engenders the biggest impact, with an 8% increase in total farm income, followed successively by the 1%Cess with +5.6% and the NoCess_Stap scenario with +4%. The NoCess_Stap scenario has less impact than the 1%Cess scenario because the share of marketed staple crops is much lower than the share of marketed cash crops. That is, an increase in production of one unit has more income effect for cash crops than for staple crops, and therefore a reduction or removal of produce cess provokes a larger increase in income for the former. From Figure 8, one can observe that: (i) all farm economic sizes benefit from the simulated reform options, to different degrees; (ii) the NoCess scenario engenders the largest farm income increase, as expected, followed by the 1%Cess scenario; and (iii) the larger the economic size, the higher the income increase. In other words, reduction or elimination of produce cess tends to favour large farms (in both absolute and relative terms) and to increase disparity among farms.

In fact, for the large farms, farm income increases by 5% to 9% depending on scenario, while for the small farms this increase is only 1.5% to 3%, despite their lower farm income in the baseline scenario. This is however not surprising, because large farms are market-oriented and thus benefit more from the reduction in produce cess compared to small farms, which are oriented more towards providing supplementary food for their households.

Figure 7: Farm income changes under simulated scenarios (percentage change relative to the baseline)

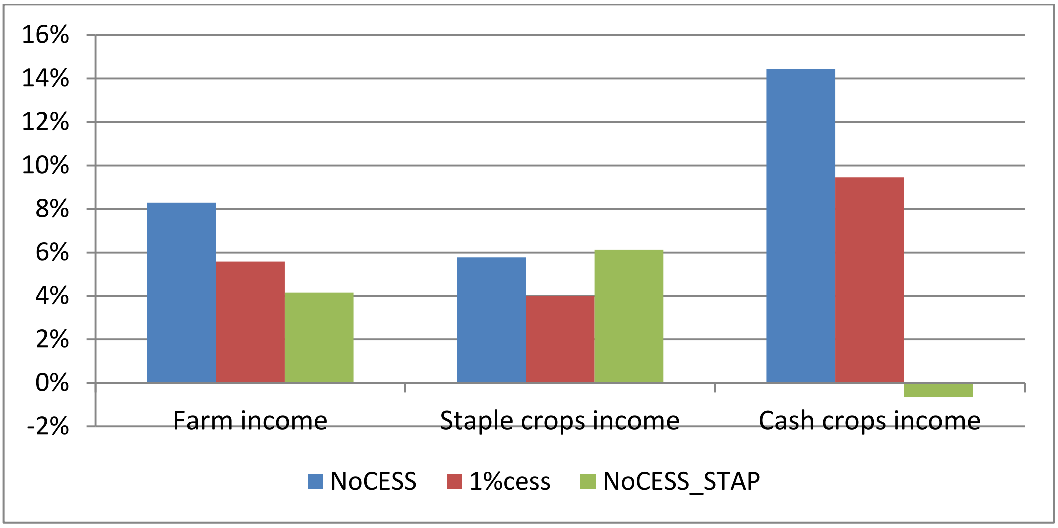


Figure 8: Farm income changes, by economic size, under simulated scenarios (percentage change relative to the baseline)

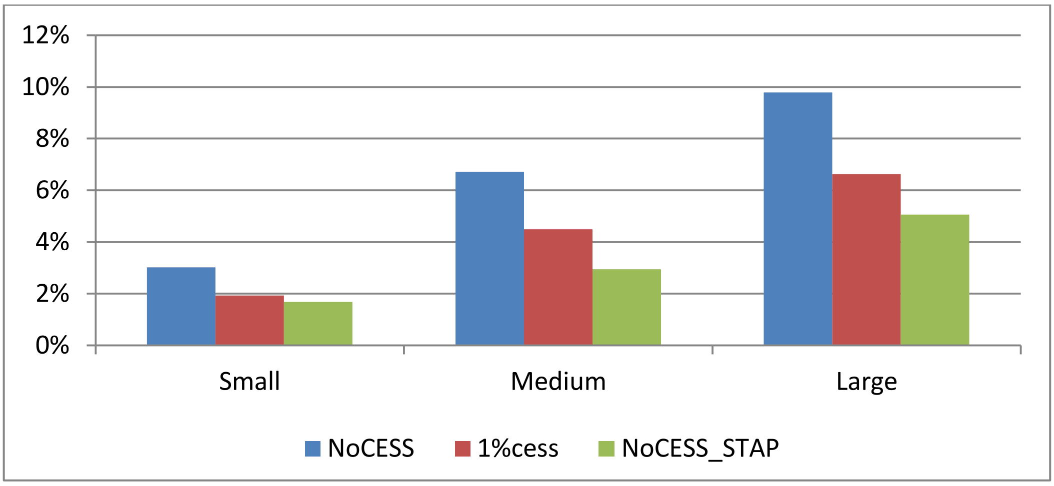
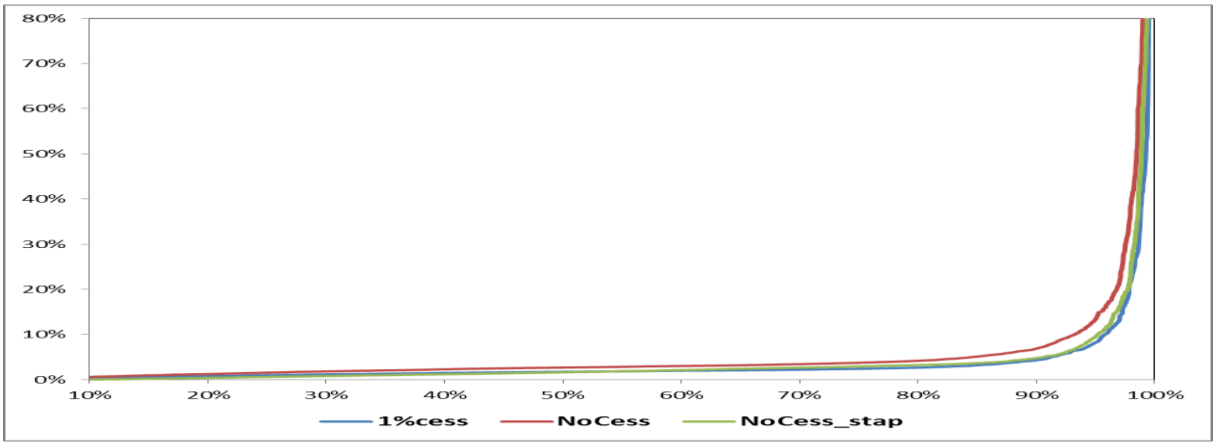


Figure 9 shows the distribution of the income change relative to the baseline, across the total farm population. Only 5% of the farms experience a substantial increase in income (more than 25%) with reduction or abolition of produce cess. For the remaining 95% of farmers, income increase is less than 10% or even close to zero, due to low market participation and/or high production costs. This figure also shows that total removal of produce cess (NoCess scenario) has the biggest positive effect on all farms (red line), in comparison to the other two scenarios which have pretty much the same distributional effects.

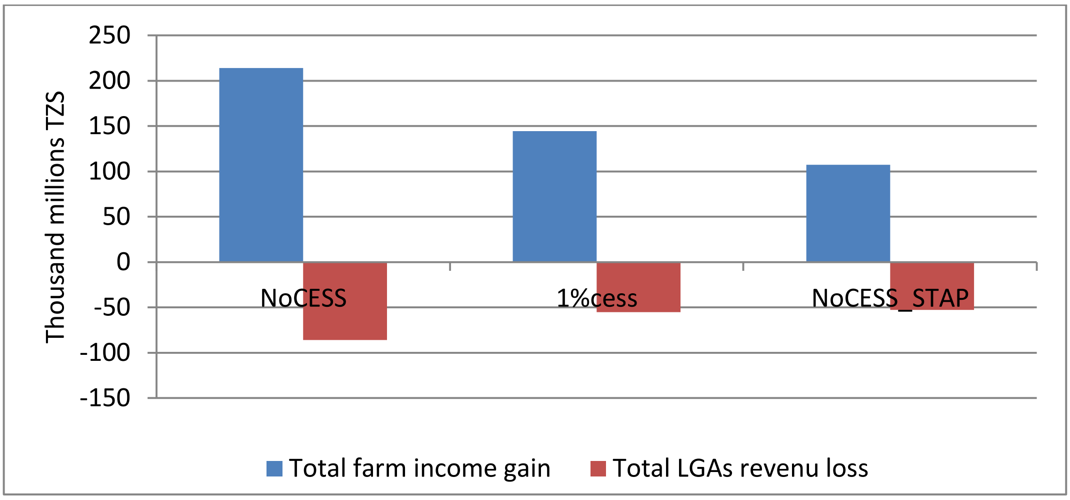
Up to now, we have only discussed the benefits of each simulated scenario, without considering the cost in terms of loss of revenue for the LGAs. Yet this is an important aspect to consider, because whatever the selected reform option, LGAs need to know the amount of revenue they will lose and how to cover it. Hence, it is important to calculate the total 'cost' of each simulated policy and compare it with the total benefit. From a cost–benefit perspective, the most efficient policy option is the one that best achieves the targeted benefit at lowest cost. We measure policy efficiency as the ratio of aggregate change in farm household income (i.e. income gain) to total costs supported by the LGAs (i.e. loss of revenue).

Figure 9: Distribution of income change caused by the simulated scenarios, across the whole farm sample (percentage change relative to the baseline)



Obviously, the scenario that provides the highest gain is also the most costly (Figure 10). Indeed, the NoCess scenario leads to a total cost of TZS 86 billion and a gain of TZS 214 billion. Interestingly, the cost of the other two scenarios are quite similar: TZS 55 billion for the 1%Cess scenario and TZS 53 billion for the NoCess_Stap scenario. However, the former scenario leads to much higher gains: the 1%Cess scenario produces a total gain of TZS 144 billion, while the NoCess_Stap scenario leads to a total gain of TZS 107 billion. Therefore, in terms of cost–benefit analysis measured through the income gain/loss of revenue ratio, the 1%Cess scenario has the best ratio (2.61), even better than the NoCess scenario (2.49). With a value close to 2, the ratio under the NoCess_Stap scenario is the lowest (Figure 10). This ratio could be understood as how much farm income increases when reducing produce cess by TZS 1.

Figure 10: Comparison of the policy scenarios in terms of total farmer gains and total LGA losses



Finally, the impacts on rural poverty and on food security are rather thin. Reduction in rural poverty ranges from -0.2% under the NoCess_Stap scenario to -0.37% under the NoCess scenario. Large farms, and farms specialized in annual cash crops and in permanent crops, register the highest change in the extreme poverty gap, ranging between -0.2% and -0.7%, because they benefit the most from reduction or removal of cess. Although reduction or removal of produce cess can be seen as a good option to enhance income, it is probably not sufficient to address rural poverty reduction, according to the model outputs. This is probably also because the scale of the tax reduction is not big enough to observe significant impact.

7 Conclusions

This report presents the farm household model FSSIM-Dev, used to assess the impacts of selected agricultural policies on farm household livelihoods, poverty levels and food security in developing countries and rural-based economies. The rationale for such a farm household model is the increasing demand for a micro-simulation tool able to model farm-specific policies, and to capture heterogeneity across farms and identify winners and losers of existing or alternative policies. The impact of a single policy may be very different depending on household location, resource endowment, land use, access to markets, economic status or family composition.

Based on positive mathematical programming, FSSIM-Dev seeks to improve the quality of policy assessment compared with existing aggregate and aggregated farm-group models, and to take into account the main characteristics of developing countries. To the best of our knowledge, the model presented here is one of the few farm household programming models which attempt to reproduce farm household production and consumption decisions in a separable regime. FSSIM-Dev has been set up such that it can easily be used to assess a broad range of policies, as well as to make efficient use of existing data from LSMS-ISA household surveys. The simulation results presented in this report for the three SSA countries (Ethiopia, Niger and Tanzania) illustrate such flexibility.

Despite its strong relevance, in both conceptual and technical terms, the FSSIM-Dev model suffers from several limitations. Firstly, output market prices are assumed to be exogenously given. This implies that market feedback (output price changes) is not taken into account in the model. Although in developing economies high transaction costs tend to isolate the various local markets from each other, and thus prevent price transmission, price effects could be important when production change is quite high. A second caveat is that we assume a fixed farm structure, implying that the model does not capture land extension in response to introduction of the policies. The third limitation is the use of a linear expenditure system which can only partially capture demand dynamics, due to marginal budget shares remaining constant over time. More flexible functional forms would be preferable. The fourth limitation is the non-consideration of environmental aspects of crop production, although they could easily be covered by FSSIM-Dev if environmental coefficients for cropping systems were available. The last limitation is the lack of critical assessment of the model's forecasting performance, due to the unavailability of data such as a second dataset for running some *ex post* analysis. Apart from using our intuition, it is very difficult to evaluate the results in a quantitative and more objective way.

Despite these limitations, which could be addressed in future research, we still consider that FSSIM-Dev can deliver finer policy analyses and provide policymakers with useful insights into how and where policy measures may be expected to be most effective.

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List of abbreviations and definitions

ACC	Agricultural Commercialization Cluster
AGLINK-COSIMO	Worldwide Agribusiness Linkage Program + Commodity Simulation Model
AME	Adult Male equivalent
CAP	Common Agricultural Policy
CSA	Central Statistics Agency
DG-DEVCO`	Directorate General for International Cooperation and Development
EDF	European Development Fund
EU	European Union
FNS	Food and nutrition security
FSSIM-Dev	Farm System Simulator for Developing Countries
GTAP	Global Trade Analysis Project
IFM-CAP	Individual Farm Model for CAP analysis
INS	Institut National de la Statistique
JRC	Joint Research Centre
LES	Linear Expenditure System
LGA	Local Government Authorities
LSMS-ISA	Leaving Standard Measurement Study Integrated Surveys on Agriculture
SPIN	Stratégie de la Petite Irrigation au Niger
SSA	Sub-Saharan Africa

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