A Strategic Framework for Adoption and Impact Studies
in the CGIAR Research Program on Maize (MAIZE)

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CGIAR RESEARCH PROGRAM ON Maize

CIMMYT International Maize and Wheat Improvement Center

IITA Transforming African Agriculture

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Vijesh V. Krishna, International Maize and Wheat Improvement Center (CIMMYT), Texcoco, Mexico.
Shiferaw Feleke, International Institute of Tropical Agriculture (IITA), Dar es Salaam, Tanzania.
Paswel Marenya, CIMMYT, Addis Ababa, Ethiopia.
Tahirou Abdoulaye, IITA, Ibadan, Nigeria.
Olaf Erenstein, CIMMYT, Texcoco, Mexico.

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1. Introduction

Maize is one of the most important food crops in the world. In 2016, global acreage of maize was 188 million ha, of which 36% (68 million ha) were in developing and low-income countries (FAOSTAT, 2018). Together with rice and wheat, it provides at least 30% of the food calories to more than 4.5 billion people in the developing world (Shiferaw et al., 2011). The role of maize to ensure rural food security is even higher in some of the least developed countries of sub Saharan Africa. For example, over 55% of the daily calorie intake of Zambian households is derived from maize alone (Khonje et al., 2015). However, maize is not only a food crop for humans. Demand of maize has increased as feed and fodder for livestock production, driven largely by the rapid economic growth in Asia and Latin America (Hellin et al., 2015). It also has significant industrial importance as a raw material for bioethanol production, also in developing countries, alongside other crops. Meeting this increasing food-feed-energy demand is one of the major challenges of maize production sectors across the developing world, which are constrained by natural resource depletion and degradation, input scarcity, climate change, and persisting poverty among the producers. Shortfalls in maize supplies and resulting increases in the food prices have grave consequences for developing countries as food will be less affordable for millions of poor consumers (Shiferaw et al., 2011). Although the maize area expansion is unprecedented in many parts of the global South, area expansion will not be a sustainable solution to meet the market demand. Increases in cultivated area often comes with an environmental cost of land degradation and biodiversity loss. There have been many compelling success stories with respect to productivity enhancement of maize, with the increased adoption of new seeds and associated technologies. These research-for-development (R4D) interventions could possibly have significant livelihood implications for both maize farmers and consumers.

The CGIAR Research Program on Maize (CRP MAIZE or simply MAIZE) is part of a concerted effort of to implement a new, results-oriented strategy in maize agri-food systems, exploiting the potential of international agricultural R4D fully to enhance global food security and environmental sustainability. Two CGIAR centers – the International Maize and Wheat Improvement Center (CIMMYT) and the International Institute for Tropical Agriculture (IITA) – have lead this CRP since late 2011. The shared challenge of the Program is to "double productivity and significantly increase the incomes and livelihood opportunities from more productive, resilient and sustainable maize-based farming systems on essentially the same land area – while contending with climate change and increasing costs of fertilizer, water, and labor" (CRP MAIZE, 2016). Through MAIZE-driven R4D, targeted crop productivity growth of 20% by 2020 and 50% by 2050 in 60 major maize producing countries should contribute to food/feed access and stable prices for over 900 million poor maize consumers. Sustainable intensification of maize production and stabilization of the total maize area at about 120 million hectares in developing countries is the second objective of MAIZE. The other impact targets are to (a) reduce the frequency of production shortfalls and price volatility in areas and countries where the probability of crop failure in maize-based farming systems is high, (b) diversify maize-based farming systems and enhance their productivity and sustainability, dealing specifically with the systems with the highest poverty concentrations, (c) ensure that higher rates of maize yield growth are sustained in the face of climate change, worsening water scarcity, and rising fertilizer prices, and (d) increase opportunities for diverse market participation. Research programs and projects built around these objectives are expected to target two groups of farmers that occupy approximately 64% of all maize area in the Global South and are home to 1.2 billion of the poor and 126 million malnourished children.

> **Target group 1 (Smallholders in stress-prone environments with poor market access):** This group is comprised of an estimated 640 million poor people, among whom an estimated 275 million are maize-dependent. These farming systems are located in South Asia, sub-Saharan Africa, and Latin America & the Caribbean.

> **Target group 2 (Market-oriented, technology-constrained smallholders in more benign environments):** This group comprises an estimated 470 million poor people, of whom 367 million are maize-dependent. These systems are located in East Asia, South Asia, sub-Saharan Africa, and Latin America & the Caribbean. (CRP MAIZE, 2016).

MAIZE aims to sustainably intensify maize-based cropping systems and provide stress resilient and nutritious maize. MAIZE includes a flagship project titled "Enhancing MAIZE's R4D Strategy for Impact". This flagship includes a Cluster of Activities (CoA) focused on adoption and impact evaluation; with other CoA's set out to strengthen foresight and targeting to enhance priority setting and planning; harness smallholder market opportunities; and mainstream gender research in MAIZE and ensure greater social inclusion in all MAIZE interventions. This FP is expected to contribute toward three Sustainable Livelihood Opportunities (SLOs), such as reducing poverty, improving food and nutrition security for health, and improving natural resource systems and ecosystem services. Readers may obtain more information on MAIZE from the website http://maize.org/, and from related proposals (CRP MAIZE, 2016; CRP MAIZE, 2011), and other strategy reports (for example cf. Badstue [2013]). This strategy document is envisioned to facilitate assessment of diffusion and impacts of MAIZE interventions by developing a better understanding of the adoption/adaptation processes associated with MAIZE technologies and differential impacts of these interventions along the impact pathway among different categories of farmers.

Documenting technology adoption and establishing the associated impacts are important for agricultural research due to two reasons. One, this provides a simple measure of performance efficiency of agricultural R4D. Both public and private sector funding for research and technology development for smallholder agriculture are keen to scrutinize whether their investments are delivering, thereby intensifying the research efforts to demonstrate value-for-money (Glover et al., 2016; Sumberg et al., 2013). Two, the lessons learnt from adoption-impact assessments can be used for subsequent improvements in agricultural R4D (Walker and Alwang, 2015; Douthwaite et al., 2003). Although a large number of studies have demonstrated that growth in agricultural productivity and reduction in rural poverty is inextricably intertwined with investments in agricultural research and extension (Pray et al., 2017; Evenson and Gollin, 2003), agriculture R4D remains to be an under-invested domain in many developing countries (Raitzer and Maredia, 2012; Hurley et al., 2014).

The present document is envisioned as a strategy framework to facilitate assessment of diffusion and impacts of MAIZE interventions. It will be constructively revised over time by including new insights and lessons learnt from implementing the strategy in practice, and latest literature on adoption and impacts of technology interventions in maize agri-food systems. In the current version, we focus on the research gaps, identified by quickly reviewing the peer-reviewed journal articles published between 2008 and 2017. The literature search is confined to the journals listed in the Web of Knowledge.

2. A conceptual framework for adoption and impact studies[1]

The main objective of the adoption-impact CoA in MAIZE is to institutionalize a formal procedure to address the increasing demand for quantifiable evidence on R4D outcomes of the CRP, following a relevant, credible, and rigorous methodology that is both financially efficient and socially inclusive. In this section, a **generic framework of adoption-impact assessment is developed**, which is expected to help position the existing literature and to explore the research gaps in the succeeding sections. This section indicates that researchers ideally face a vast array of choices while measuring adoption and/or impact of technology interventions (e.g., different metrics of outcome measures). The framework is expected to help the MAIZE team to better prioritize the research activities based on evidence and feedback from the field. A pictorial representation of adoption-impact assessment framework is provided in Appendix 1. Here a connection between investment in maize R4D and development of agrarian economy through a number of intermediary steps is depicted. The impact assessment in MAIZE envisages a two-tier assessment of interventions – at macro as well as micro-levels.

Directly linking R4D investments to economic growth is a common procedure in the **macro-studies** to evaluate the investments (Pardey et al., 2016; Hurley et al., 2014). A number of studies have examined how public and private sector agricultural R4D reduces poverty, alleviates malnutrition, and reduces livelihood vulnerabilities, through new crop and livestock technologies that increase the quantity and quality of agricultural output per unit of land, labor and other resources (Pray et al., 2017; Byerlee and Dubin, 2010). In general, at an aggregate level, investment in agricultural R4D is estimated to have significantly high returns (Alston et al., 2012; Renkow and Byerlee, 2010). However, some researchers have observed that the **distribution of impacts from agricultural research is highly skewed** and the **high rates of return calculated for individual cases of success are unlikely** to be representative of the overall research portfolios (Maredia and Raitzer, 2010). The benefits from individual investments vary widely and targeting of investments is required to generate the greatest possible livelihood and/or environmental effects. This necessitates a systematic and comprehensive coverage of research investments and research prioritization within the CGIAR and beyond.

One of the most **prominent macro studies** on maize was conducted by Alene et al. (2009), which measured the impacts of maize research in **West and Central Africa from 1981 to 2005**. Adoption of improved maize varieties reportedly increased from less than 5% to 60% between the 1970s and 2005, and yielded an aggregate rate of return on R4D investment of 43%. As a result, more than one million people per year moved out of poverty since the mid-1990s. Over half of these impacts were attributed to the international maize research. *More studies are required in this direction, focusing on aggregate impact of MAIZE interventions across the developing world, by keeping a systematic inventory of technology releases, area coverage of individual technologies, and aggregate changes in the rural economy and farmers' livelihoods that are attributable to the R4D investment made*. A distinctive outcome of such effort is expected to be evidenced in a soon-to-be-released report on the aggregate impacts of international maize germplasm research.

Micro-level studies, on the other hand, are published profusely. They provide relevant information to clarify the impact pathways and to trace out the constraints in scaling out technologies. Keeping track of the spread of technologies derived from R4D investment is the first step toward effective monitoring and impact evaluation. Slow rate of scaling out of technologies in smallholder farming systems is often cited as the key factor explaining stagnating agricultural yields (Pamuk et al., 2014). This warrants in-depth adoption studies detailing the constraints of adoption. There are two main factors that complicate the adoption analysis: (i) diversity of forms of agricultural interventions that prevents application of generic analytical methods, and (ii) constant reinvention of technologies by farm households. Based on the form, technology interventions could be biological (e.g., improved varieties), chemical (e.g., herbicides), mechanical (e.g., seed drill), agronomic (e.g., intercropping), informational (e.g., market selection) or a combination (Sunding and Zilberman, 2001), and the methodology of adoption studies varies accordingly. The second complexity in adoption studies is that farmers continuously reconstruct the technological information they were passed on (Douthwaite et al., 2003), and this reinvention results in an array of non-uniform technological inputs in a process mediated by a multitude of social factors and constraints. As a result, we could

1 This section addresses the conceptual framework based on which adoption and impact studies are implemented in developing country agriculture. Not being crop-specific, it overlaps with the framework developed for adoption-impact strategy in CRP WHEAT.

observe partial adoption of certain elements, dis-adoption and discontinuous adoption other than the dichotomy of full and non-adoption. Measures of adoption may also indicate either or both the timing and extent of new technology utilization by farm households. This inherent complexity of adoption studies is reflected in the statement by (Sunding and Zilberman, 2001):

> **"Adoption behavior may be depicted by more than one variable. It may be depicted by a discrete choice, whether or not to utilize an innovation, or by a continuous variable that indicates to what extent a divisible innovation is used. For example, one measure of the adoption of a high-yield seed variety by a farmer is a discrete variable denoting if this variety is being used by a farmer at a certain time; another measure is what percent of the farmer's land is planted with this variety." (p. 229).**

The adoption decision is represented in Appendix I as continuum between (a) immediate and continuous adoption of all technology components on the whole farm (or at least all relevant crop plots), to (b) non-adoption of any technology-component. In line with the 'Process of Agricultural Utilization Framework' proposed by Brown et al. (2017), this continuum contains a number of different combinations to classify various types of use and non-use of technology, rather than simple dichotomous choice. The adoption studies are expected to make conscious efforts to capture this complexity while evaluating the spread of innovations in the agri-food systems. Future adoption studies in MAIZE are proposed to address the behavioral (e.g., role of risk aversion) and institutional (e.g., land tenure) factors, complementarities between newly introduced and already existing technologies, and subjective expectations of farmers on impact of the technology. There is a vast literature that describes the observable heterogeneity of farming communities that restricts scaling out of technologies. Various studies across developing countries have highlighted the unavailability and untimely delivery of the technologies and unfavorable climactic conditions as adoption constraints (Suri, 2011). In addition, an active investigation is required on the supply side factors, such as the role of policy environment and extension methods, in order to design effective and inclusive dissemination strategies.

Adoption studies are often complemented by ex-post impact evaluations that quantify the economic and social outcomes of the technology intervention (Maredia et al., 2014). Once the adoption rates are calculated, the impact assessments would involve estimating a single parameter – the average effect size. However, the process of estimation of effect size is not even remotely straight forward or simple. Depending on the nature of the technology and the socio-economic, institutional and agro-ecological conditions, farmers' adoption decisions could lead to a multitude of outcomes, even including some undesirable or unforeseen ones. Depending on the research question at hand, the time frame of impact pathway, and the size and scale of intervention, the methodological approach to attribute the outcomes to intervention varies widely – from partial equilibrium economic surplus models to social accounting matrices and micro-econometric modelling. The methodological difficulty to establish causality is much higher compared to estimation of associations or correlations.

Against the above mentioned backdrop, a major task of the MAIZE adoption and impact CoA is to **evaluate technology impacts in maize agri-food system with methodological rigor**. Adoption of a technology might reduce the use of certain inputs while increasing others, increase output quality and quantity, reduce yield variability, and/or enhance environmental services from the production systems (cf. Appendix I). Many of these changes would reflect in the livelihoods of farmers and service providers (e.g., agricultural laborers, machine services etc.). If the demand for inputs changes in a large scale, it could even affect the demand for locally produced commodities and hence the output price. The possibility of existence of such multiple impact pathways makes estimation of aggregate effect of a technology both complex and non-linear. A number of studies have noted that no single framework or methodology could fit all impact evaluation exercises simultaneously. Based on this realization, the CoA will actively **engage in identification of potential impact pathways in the maize agri-food systems.** Emergent understanding on scaling up and scaling out of technologies necessitates a constructivist paradigm of rural development, in which farmers take part in the learning process actively and construct knowledge by fitting technological information in to their existing world view. The impact evaluation **requires diverse evaluation methods** (e.g., qualitative, participative) **complementary to the conventional economic impact assessment methods** (Douthwaite et al., 2003). Part of the research will therefore be carried out by quantitative and qualitative social scientists in collaboration, and by using participatory research approaches to inform the adaptation of MAIZE innovations especially at the initial stages of their development, scaling, and adoption.

3. A quick review of adoption studies in maize systems (2008-2017)

Why are some farmers reluctant to take up apparently useful agricultural technologies in developing countries? A large number of empirical studies seek to answer this question analyzing farmer decision-making process. The notion of adoption as a process governing the utilization of innovations (Sunding and Zilberman, 2001) is central for a coherent understanding on technological change in agriculture. Feder et al. (1985) had outlined the conventional methodology of adoption studies, which includes representing adoption as using a dummy variable, selecting a number of potential explanatory variables, and testing the statistical relevance of each the explanatory variable running logistic or probit regression models. Glover et al. (2016) criticizes this approach, which is commonly used in development research literature and practice, indicating that it leads to inaccurate and misleading conclusions. Addressing the agricultural research in Africa, the authors opine that the concept of adoption used in many studies are "too linear in both spatial and temporal terms, too binary, too focused on individual decisions, and blind to many important aspects of technological change" (Glover et al., 2016).

Even three decades after publishing the seminar review paper of Feder and his colleagues, the **approach of adoption studies in agricultural field has not changed significantly.** This criticism raised by Glover et al. (2016) could be directed toward a large share of adoption studies taking place in maize agri-food systems. Technological changes are depicted by relatively simple farmer choice that can be represented by a dichotomous variable, often overlooking farmer's learning process shaped by his/her socio-cultural context. Many of the adoption studies inherently assume technological change as replacement of old inferior practices with new superior ones, and thereby inherently incapable to address the processes of adaptation, creolization, hybridization and incorporation (Glover et al., 2016; Douthwaite et al., 2003; Douthwaite et al., 2001). In this section, we quickly review the studies addressing the diffusion of technologies in maize agri-food systems during 2008-2017. During this decade, maize agri-food systems attracted significant research funds, with projects like Sustainable Intensification of Maize-Legume Cropping Systems for Food Security in Eastern and Southern Africa (SIMLESA; http://simlesa.cimmyt.org/) and Drought Tolerant Maize for Africa (DTMA; http://dtma.cimmyt.org/). Possibly as a result of this increased R4D attention, **a number of research papers have been published providing a rich database on technology adoption in maize. During the 2008-2017 period, about 75 studies** that used data from **approximately 116 thousand farm households** addressed technology adoption in maize agri-food systems (Table 1).

An examination of the adoption studies conducted in maize agri-food systems indicates that the **studies were predominantly (a) conducted in sub-Saharan Africa, (b) examining varietal and sustainable intensification technologies, and (c) using adoption dummies to represent technological change in econometric models**. One set of studies assessed adoption of particular technologies in isolation, while another group dealt with adoption of multiple technologies and explored trade-offs and complementarities between technologies. Several studies carried out adoption analysis just as a pre-requirement of impact assessment. These studies measured adoption as a dichotomous variable on the use of specific technologies, and modeled the determinants of adoption with a conventional set of socio-demographic variables. A typical example of a study of this genre is Lunduka et al. (2017). Using a survey of 200 households in Zimbabwe, the authors examined farmers' adoption of drought tolerant maize varieties and estimated the impact of adoption on total maize production using a control function approach. Alwang et al. (2017), Hassan et al. (2016), Ngwira et al. (2014), Tambo and Abdoulaye (2012) and Alene et al. (2008) went a step further and assessed the factors contributing not only to the probability of adoption, but also the intensity of adoption (e.g., area under the technology).

While the adoption analysis for impact assessment has its own relevance, these studies often do not provide intricate details on farmer decision-making process, and end up overlooking the complexities of adoption decision. However, there exist **a number studies on maize agri-food systems that analyzed varietal adoption in depth, looking at farmer awareness and preferences as the key determinants**. For example, Kassie et al. (2017) recognized the importance of farmers' perceptions to determine adoption of drought-tolerant maize varieties and estimated the implicit prices farmers are willing to pay for the attribute. Groote et al. (2016) identified farmer familiarity with quality protein maize (QPM) and awareness on the nutritional and agronomic benefits of the technology as the key determinants of the adoption decision. Kathage et al. (2016) similarly examined the role of farmer awareness to model

Table 1. Technology adoption studies in maize production systems (2008-2017)

Study	Country	Technology	Sample size (# households)	Analytical tool	Remarks
Varieties					
Alwang et al. (2017)	Ethiopia	improved varieties	1,253	double hurdle model	models probability and intensity of adoption
Kassie et al. (2017)	Zimbabwe	drought tolerant varieties	1,400	choice experiment, multinomial logit	elicitation of preferences and willingness to pay
Sapkota et al. (2017)	Nepal	foundation seed production	182	probit	determinants of household involvement in seed production
Lunduka et al. (2017)	Zimbabwe	drought tolerant varieties	200	probit	adoption estimation for impact assessment
Makate et al. (2017b)	Zimbabwe	drought tolerant varieties	601	probit	adoption estimation for impact assessment
Wang et al. (2017)	Kenya	hybrid maize	444	ordinal logit	factors that affect the adoption of hybrid maize varieties
Wossen et al. (2017)	Nigeria	drought tolerant varieties	2,084	binomial	adoption estimation for impact assessment
Groote et al. (2016)	Ethiopia, Kenya, Tanzania, Uganda	biofortified maize	962	matching	effectiveness of extension strategies for increasing adoption
Kansiime et al. (2016)	Uganda	improved varieties	90	multinomial logit	role of seed sources on adoption of improved varieties in maize, cassava and beans
Manda et al. (2016b)	Zambia	improved varieties	810	probit	adoption estimation for impact assessment
Qiu et al. (2016)	China	modern varieties	621	Tobit, Negative Binomial	probability of adopting new varieties and number of new varieties adopted
Beyene and Kassie (2015)	Tanzania	improved varieties	681	duration analysis	determinants of the speed of adoption
Fisher et al. (2015)	Ethiopia, Tanzania, Uganda, Zambia, Zimbabwe, Malawi	drought tolerant varieties, other improved varieties	3,700	multinomial logit	examines barriers to adoption
Fisher and Carr (2015)	Uganda	drought tolerant varieties	408	multinomial logit	on gendered roles and responsibilities influencing adoption
Coromaldi et al. (2015)	Uganda	improved varieties	2,124	probit	adoption estimation for impact assessment
Ghimire and Huang (2015)	Nepal	improved varieties	416	double hurdle	estimates the effect of wealth on adoption
Holden and Fisher (2015)	Malawi	drought tolerant varieties	350 (panel)	linear probability	role of subsidies to promote adoption
Kathage et al. (2016)	Tanzania	hybrid maize	695	treatment-effect model	role of awareness on adoption
Khonje et al. (2015)	Zambia	improved varieties	810	logit	adoption estimation for impact assessment
Zeng et al. (2015)	Ethiopia	improved varieties	1,359	probit	adoption estimation for impact assessment
Bezu et al. (2014)	Malawi	improved varieties	1,375 (panel)	double hurdle with correlated random effects	adoption estimation for impact assessment; models probability and intensity of adoption
Beshir and Wegary (2014)	Ethiopia	hybrid maize	277	logit	adoption in the drought-prone regions
Smale and Olwande (2014)	Kenya	hybrid maize	1,578 (panel)	Tobit model with correlated random effects	farmer demand for hybrid seeds
Fisher and Kandiwa (2014)	Malawi	improved varieties	9,571	logit	effect of input subsidies on adoption
Fisher and Snapp (2014)	Malawi	improved varieties	200	generalized ordered logit	association between farmer perception of drought risk and adoption and continued use of technology

Study	Country	Technology	Sample size (# households)	Analytical tool	Remarks
Kassie et al. (2014)	Tanzania	improved varieties	680	generalized propensity score, Tobit	adoption estimation for impact assessment; estimates intensity of adoption
Mason and Smale (2013)	Zambia	hybrid maize	3,231 (panel)	correlated random effects truncated normal hurdle	adoption estimation for impact assessment
Abera et al. (2013)	Ethiopia	improved varieties	240	descriptive	constraint analysis
Tambo and Abdoulaye (2012)	Nigeria	drought tolerant varieties	200	double hurdle, Tobit	models probability and intensity of adoption
Lunduka et al. (2012)	Malawi	improved varieties	171	Tobit	linking specific attributes of different varieties to adoption
Mabah and Oyekale (2012)	Cameroon	technical package (improved varieties, fertilizers, pesticides, mono-cropping)	52	logit	determinants of adoption
Arslan (2011)	Mexico	traditional cultivars	280	fractional logit	role of non-market values on adoption
Bellon and Hellin (2011)	Mexico	hybrid and traditional cultivars	301 (panel)	random effects Tobit	shifts in area and number of farmers planting hybrids and landraces
Tura et al. (2010)	Ethiopia	improved varieties	120	bivariate probit	adoption and continued use
Langyintuo and Mungoma (2008)	Zambia	improved varieties	300	double hurdle model	effect of household wealth on adoption
Varieties with other technologies					
Abay et al. (2017)	Ethiopia	improved seeds, chemical fertilizers, extension services	14,762	random coefficients multivariate probit model	complementarities and unobserved heterogeneities in technology adoption
Koppmair et al. (2017)	Malawi	sustainable agricultural practices	1,647	multivariate probit	effect of input subsidies on adoption of resource conservation technologies
Kotu et al. (2017)	Ghana	sustainable agricultural practices	1,284	multivariate probit	on interdependence of adoption decisions
Arslan et al. (2017)	Tanzania	sustainable agricultural practices	977	multivariate CRE probit	tradeoffs and complementarities in technology adoption
Ragasa and Chapoto (2017)	Ghana	improved variety, purchased seeds, inorganic fertilizers	630	trivariate probit	estimated profitability of fertilizer use with and without subsidy
Theriault et al. (2017b)	Burkina Faso	sustainable agricultural practices	2,700 (panel)	multivariate probit	tradeoffs and complementarities in technology adoption; gender differences in adoption
Wainaina et al. (2016)	Kenya	sustainable agricultural practices	1,344	multivariate probit	tradeoffs and complementarities in technology adoption
Magrini and Vigani (2016)	Tanzania	chemical fertilizers, improved varieties	1,543	logit	adoption estimation for impact assessment
Manda et al. (2016a)	Zambia	sustainable agricultural practices	810	mixed multinomial logit	adoption estimation for impact assessment
Mutenje et al. (2016)	Malawi	improved varieties, storage, soil and water management	892	mixed multinomial logit	adoption of multiple technologies; adoption estimation for impact assessment
Mugi-Ngenga et al. (2016)	Kenya	climate change adaptation strategies	200	multinomial and binary logit	determinants of household strategies to adapt to climate variability

Study	Country	Technology	Sample size (# households)	Analytical tool	Remarks
Kassie et al. (2015a)	Ethiopia, Kenya, Malawi, Tanzania	sustainable intensification	5,779	multivariate probit	explores smallholder farmers' adoption decisions of multiple technologies
Mathenge et al. (2015)	Kenya	chemical fertilizers, hybrid seeds	1,578	double hurdle models	effect of off-farm employment on technology adoption
Ricker-Gilbert and Jones (2015)	Malawi	storage technology, improved varieties	462 (panel)	panel linear probability model, probit with Mundlak–Chamberlin device	examines whether farmer access to post-harvest storage technology affects adoption of improved varieties
Ndiritu et al. (2014)	Kenya	sustainable intensification	578	multivariate probit	gender differences in adoption
Ainembabazi and Mugisha (2014)	Uganda	several (unspecified) technologies	356 (panel)	panel Tobit, bivariate model	investigates the relationship between adoption of and experience with agricultural technologies
Abebaw and Haile (2013)	Ethiopia	chemical fertilizers, improved varieties, pesticides	965	propensity score matching	effect of cooperative membership on technology adoption
Kassie et al. (2013)	Tanzania	sustainable agricultural practices	681	multivariate probit	tradeoffs and complementarities in technology adoption
Teklewold et al. (2013a) Teklewold et al. (2013b)	Ethiopia	sustainable agricultural practices	898	multivariate and ordered probit	tradeoffs and complementarities in technology adoption
Cunguara and Darnhofer (2011)	Mozambique	improved varieties, mechanization, storage	6,149	logit	adoption estimation leads to impact assessment
Non-varietal technologies					
Brown et al. (2017)	Ethiopia, Kenya, Tanzania, Malawi, Mozambique	conservation agriculture	6,559	not applicable	disaggregated adoption process into ten stages.
Marenya et al. (2017)	Ethiopia, Kenya, Tanzania and Malawi	minimum tillage	11,188	probit	adoption predicted using household and policy variables
Makate et al. (2017a)	Zambia, Malawi, Mozambique	sustainable agricultural practices	312	linear regression	adoption estimation for impact assessment
Manda et al. (2017)	Zambia	crop rotation	810	probit	adoption estimation for ex ante impact assessment
Ng'ombe et al. (2017)	Zambia	conservation farming	7,512	multinomial logit	adoption estimation for impact assessment
Ricker-Gilbert and Jayne (2017)	Malawi	inorganic fertilizers	462 (panel)	normal hurdle, with Mundlak-Chamberlain device	long-run effects of fertilizer subsidy programs on fertilizer demand
Abdulai (2016)	Zambia	conservation agriculture	408	probit	adoption estimation for impact assessment
Hassan et al. (2016)	Nigeria	striga (weed) management	643	double hurdle	models probability and intensity of adoption.
Jaleta et al. (2016)	Ethiopia	minimum tillage	290	probit	adoption estimation for impact assessment
Lambert et al. (2016)	Lesotho	conservation agriculture	432	probit	studies farmer responsiveness to maize prices and fertilizer costs
Tesfaye and Seifu (2016)	Ethiopia	climate change adaptation strategies	296	multivariate probit	analyzes the factors that influence the choice of adaptation strategy by smallholder farmers
Murage et al. (2015)	Kenya, Ethiopia, Tanzania, Uganda	striga (weed) management	461	Tobit	gender-specific perceptions on adoption
Ngwira et al. (2014)	Malawi	conservation agriculture	300	double hurdle	models probability and intensity of adoption

Study	Country	Technology	Sample size (# households)	Analytical tool	Remarks
Kamau et al. (2014)	Kenya	soil fertility management	1,001	multivariate probit, Tobit	addresses several correlated outcomes jointly and interdependence among factors that influence their adoption
van den Broeck et al. (2013)	Mexico	conservation agriculture	282	selection model	models awareness and adoption
Jaleta et al. (2013)	Kenya	residue use	613	bivariate ordered probit	tradeoffs in crop residue utilization in mixed crop–livestock systems
Amare et al. (2012)	Tanzania	legume intercropping	613	seemingly unrelated probit, recursive bivariate probit, double hurdle, and Tobit	joint decision making in pigeon pea–maize production
Murage et al. (2011)	Kenya	striga (weed) management	491	duration model	how different dissemination pathways impacted on farmers' time to adoption
Kassie et al. (2009)	Ethiopia	conservation agriculture, compost	130	multinomial logit	factors influencing adoption of sustainable agricultural practices
Mazvimavi and Twomlow (2009)	Zimbabwe	conservation agriculture	232	Tobit	factors influencing adoption intensity
Alene et al. (2008)	Kenya	fertilizer	802	selection model	on adoption and intensity of fertilizer use

adoption of improved maize varieties using farm-household data from Tanzania. Fisher and Snapp (2014) examined the association between farmers' perception of drought risk and their adoption and continued use of modern maize in Malawi. Another notable study is Arslan (2011), in which varietal adoption in Mexico was explained based on shadow prices that capture the non-market values farmers attach to crop production. Nevertheless, there are **not many studies conducted on the role of perceptions on adoption of non-varietal technologies**. An exception is Murage et al. (2015), which evaluated gender specific perceptions and the extent of adoption of a climate-smart technology in sub-Saharan Africa. Another notable study is van den Broeck et al. (2013), in which farmer awareness was modelled as a prior step to study adoption of conservation agriculture in Mexico.

A surprisingly **large number of studies were addressing the trade-offs and complementarities between different sustainable intensification technologies**. These studies have captured farmer adoption of a number of technologies and modelled them mainly using multivariate probit or multinomial logit models. Abay et al. (2017), Koppmair et al. (2017), Kotu et al. (2017), Arslan et al. (2017), Tesfaye and Seifu (2016), Wainaina et al. (2016), Kassie et al. (2015a), Kamau et al. (2014), Kassie et al. (2013) and Amare et al. (2012) are examples of studies of this genre.

There are some, albeit **less in number, studies that addressed the inclusion dimension in the technology diffusion process.** The notion of inclusive development is becoming increasingly popular in both academic and policy literature, and with Agenda 21 and the Sustainable Development Goals (SDGs) of the United Nations it has emerged as a global development goal (United Nations, 2017). MAIZE also considers inclusive development as a key goal. Ghimire and Huang (2015) examined the effect of household wealth of adoption and use intensity of improved maize varieties in Nepal. Similarly, Langyintuo and Mungoma (2008) estimated adoption models for improved, high yielding maize varieties after stratifying households as poor and well-endowed ones based on their access to productive assets. In the gender dimension, adoption decisions were examined against gendered roles and responsibilities by Theriault et al. (2017b) in Burkina Faso, Fisher and Carr (2015) in Uganda, Murage et al. (2015) in Kenya, Ethiopia, Tanzania, and Uganda, and Ndiritu et al. (2014) in Kenya. These studies provide ample evidence for how adoption and adoption determinants differ by gender of the farmer. One of the tools of inclusive and rapid diffusion of technologies is provision of input subsidies, which was examined by a number of studies (e.g., Freudenreich and Mußhoff, 2017; Koppmair et al., 2017; Ragasa and Chapoto, 2017; Ricker-Gilbert and Jayne, 2017; Holden and Fisher, 2015; Fisher and Kandiwa, 2014; Smale et al., 2014; Chibwana et al., 2012; Marenya et al., 2012).

4. Adoption studies in MAIZE: Challenges and opportunities

Future adoption studies in maize agri-food systems must make **better use of the abundance of already published studies**. In 2017 itself about 18 adoption studies were published in international peer-reviewed journals, all of them conducted in sub-Saharan Africa. Researchers might find it difficult to establish novelty of their research, or to answer "what is new". More research is required in the maize production systems of South and Southeast Asia and Latin America. Alongside diversifying the study area, future adoption studies in MAIZE could focus on increasing data quality (i.e., reducing measurement error) and reducing dependence on household surveys for data. Potential ways to do so are explained below.

- One of the limitations of the varietal adoption studies is the **difficulty to identify maize varieties grown on farm**. Errors and mismatches are common in a research that relies either on farmer recall of varieties or on expert opinion. Adoption studies could benefit greatly from more precise characterization of germplasm in the farmers' field through techniques like DNA fingerprinting. The measure is also important to **evaluate the changes in genetic diversity of crops**, because a decline in genetic variability might reduce the plasticity of crops to respond to biotic and abiotic changes, including drought, pathogen populations, or agricultural practices. This measure will also help recognize low quality seeds in the maize seed market, presence of which leads to significant yield declines. Under the Strengthening Impact Assessment in CGIAR (SIAC) program, a number of tests are commissioned to compare DNA fingerprinting data against expert opinion elicitation data and survey based methods. For maize, experiments were conducted in Uganda (n = 550) under the SIAC program, and are being explored in Ethiopia by CIMMYT and partners with support from the Bill and Melinda Gates Foundation. The procedure for maize requires further testing and standardization, as it is a cross-pollinated crop.

- New data collection methods like satellite imageries and use of unmanned aerial vehicles (UAVs) could be effectively employed to generate data on adoption of cropping practices. Satellite imageries could retroactively provide indicators and estimates of vegetation changes (Lobell et al., 2013). The potential of UAVs to acquire images from low altitudes has not yet been utilized in the adoption studies (e.g., to identify cropping patterns). The UAS are shown to have advantages of having lower cost of operation, higher picture resolution, and high flexibility in image acquisition programming (Zhang and Kovacs, 2012).

- A major factor that prevents widespread adoption studies is that the **conventional method of household-level data collection is highly demanding with respect to money and time**. A substantial lag between data collection and publication of results reduces the value of these studies to monitoring the technology dynamics. Erenstein (2010) explores the use of village surveys as a rapid and less resource intensive complement. The secondary datasets (e.g., Situation Assessment Survey in Indian Agriculture by Government of India, Living Standards Measurement Study - Integrated Surveys on Agriculture or LSMS-ISA by the Development Economics Research Group of World Bank) also provide some useful information. The study Coromaldi et al. (2015) is an example to use available data effectively to study technology adoption. From 2009/2010 LSMS-ISA data of Uganda, information on rural household characteristics, crops cultivated, agricultural input use, production costs and availability of extension services were gathered. Since the LSMS-ISA dataset was geo-referenced, Coromaldi and his colleagues could link it with climatic and soil data, which were obtained from the National Oceanic and Atmospheric Administration and the European Centre for Medium Range Weather Forecasts.

- Apart from enhancing precision in data collection, MAIZE could put **greater emphasis on less-studied but socially relevant aspects of diffusion process, such as social inclusion, access to production resources, and economic inequalities**. Albeit being an area for public action, diffusion of disembodied innovations need not be always inclusive. Some of the disembodied innovations may not be scale-neutral, and marginal and small farmer may not find adoption profitable. Farmers may also differ with respect to their risk bearing abilities. There could also be social factors preventing certain sections of farm household to access publicly available information. Furthermore, adoption of some of the disembodied innovations requires coupling with embodied innovations (e.g., herbicides for conservation agriculture), and adoption of the latter is determined by multiple binding constraints on part of farm households and factor market imperfections (Shiferaw et al., 2015). The existing resource inequalities could affect diffusion of agricultural technologies (Zeng et al., 2018); diffusion process unless effectively targeted toward the marginalized could worsen these inequalities in the society. Only a small subset of adoption studies incorporate the social and economic heterogeneities in the analysis, although many suggest the relevance of these variables in shaping the adoption pattern.

- There has been **only limited effort to investigate the relevance of technology attributes itself in determining the scaling out patterns**. Most of the existing adoption models focus on farmer attributes and altogether omit the technology traits. Technology fitness – degree to which attributes of a technology favor its adoption and use – gains greater importance as technology and production systems become more complex (Douthwaite et al., 2001). Similarly, understanding the adoption problem from a system perspective is highly warranted. As observed by Glover et al. (2016), oversimplification of research problems in adoption studies, to make them amenable for econometric analysis, often provides an inaccurate and misleading picture for the policy makers and evaluators.

The criticism of conservation agriculture (CA) studies in southern Africa by Andersson and D'Souza (2014) is valid in this connection. "Current CA adoption studies are methodologically weak, as they are biased by the promotional project context in which are carried out, and build on farm-scale analyses of standard household surveys. A more thorough analysis of farming households and their resource allocation strategies is required to understand the farm-level adoption constraints different types of farmers face. As contextual factors appear key influences on smallholders' farming practices, studies focusing on the wider market, institutional and policy context are also needed".

5. A quick review of impact studies in maize systems (2008-2017)

Over the last decade, maize production systems as well as the nature of demand for maize have experienced significant changes across the developing world (Shiferaw et al., 2011). Climate change is posing a greater threat. High levels of climatic variability, involving changes in distribution of rains and resource scarcity, are becoming more evident in maize production systems (Kassie et al., 2015b). In response to such challenges, maize R4D investment continued to generate and disseminate different climate-smart technologies and innovations, such as drought-tolerant varieties and conservation agriculture practices (Makate et al., 2017b). Here we examine the adequacy of the literature on measuring the effects of the technological interventions published in peer-reviewed journals during 2008-2017. The technological interventions subjected to evaluation can be categorized into varietal (e.g., drought-tolerant varieties), soil fertility management (e.g., inorganic fertilizers), sustainable intensification (e.g., crop rotations) and others (e.g., metallic silos). The list of studies is given in Table 2.

Unsurprisingly, the key metric against which the impact of technological intervention is measured is grain yield (Arslan et al., 2017; Burke et al., 2017; Holden and Fisher, 2015), which is relatively easy to capture and to model. However, a large number of studies went further to assess the impacts in terms of financial and livelihood changes. For example, Kassie et al. (2018) and Zeng et al. (2015) examined the technological impact on production costs, while Kotu et al. (2017) and Makate et al. (2017a) evaluated sustainable intensification in terms of changes in farmers' net income. Khonje et al. (2015) and Coromaldi et al. (2015) studied the effect of improved maize varieties on net revenue. Going one-step further, many examined the livelihood impacts of technological interventions directly. The changes in household income and consumption were the most common livelihood indicators used in the literature (Chepchirchir et al., 2017; Makate et al., 2017a; Wainaina et al., 2017; Manda et al., 2016a; Bezu et al., 2014; Cunguara and Darnhofer, 2011). Changes in food security as the effect of adoption of improved varieties were studied by Kassie et al. (2014) and (Magrini and Vigani, 2016) in Tanzania. Poverty effects of maize technologies were evaluated by Chepchirchir et al. (2017), Abdulai (2016), Khonje et al. (2015), Mathenge et al. (2014), Smale and Mason (2014), and Becerril and Abdulai (2010). The other metrics used in the impact studies were efficiency (Abdulai and Abdulai, 2017; Ndlovu et al., 2014), production risk (Awondo et al., 2017; Wossen et al., 2017; Kassie et al., 2015b), assets (Smale and Mason, 2014), inequality (Mathenge et al., 2014; Mason and Smale, 2013), storage loss (Gitonga et al., 2013), and child nutrition (Zeng et al., 2017; Manda et al., 2016b). While some studies have examined the changes in maize consumption (Bezu et al., 2014), no study was conducted in the last 10 years on changes in nutrient intake. The effects on livestock production, as maize provides feed and fodder, were also overlooked.

Establishing causality. Analysis of empirical data on technological interventions in agriculture often rely on descriptive and regression analyses to establish association between intervention and outcome. However, the existence of an association does not necessarily imply causation. Unless technology dissemination takes place in a randomized experiment, farmers decide themselves whether to adopt the technology or not, making technology adoption a non-random process. Comparing the outcomes between adopting and non-adopting farm households may be misleading as these groups may differ systematically. That means the measure of association between intervention and outcome might be distorted due to a sample selection that does not accurately reflect the target population. Even a regression model that contains technology adoption as a treatment variable and controls for the use of other inputs and household attributes cannot completely rectify this bias as there could still be certain unobserved heterogeneity. The empirical challenge in impact assessment using observational studies is establishing a suitable counterfactual against which the impacts are to be estimated.

The standard statistical procedure to deal with selection bias is instrumental variable approaches with two-stage least squares or generalized method of moments. Estimation using instrumental variables allows for the identification of the impact of exogenous changes on technology adoption, and eliminates the effect of reverse causation or simultaneity. However, suitable instrumental variables are not readily available, and many times the choice of the instruments is debatable. Awondo et al. (2017), Arslan et al. (2017), Burke et al. (2017), Zeng et al. (2017), and Mathenge et al. (2014) used instrumental variable regression to address endogeneity bias associated with technology adoption decision.[2] Another method is the control function, which is a statistical method to correct for endogeneity bias relying on the same kinds of identification conditions as in two-stage least squares or generalized method of moments, but by modelling the endogeneity in the error term. Plugging in fitted values for the endogenous variable in the second stage or using two-stage least squares regression only works well in the case where the first regression is linear. When technology adoption is binary, this will lead to inconsistent estimation in the second stage. However, the control function approach fits this more appropriately. Lunduka et al. (2017), Holden and Fisher (2015), Bezu et al. (2014), Smale and Mason (2014), and Mason and Smale (2013) had deployed control function approach to model potential endogeneity bias of technology adoption.[3]

All of these studies have shown that the instrumental variables are strongly correlated with the suspected endogenous explanatory variable. However, one may suspect that some of these instruments (footnotes 2 and 3) might not satisfy the exclusion restriction as they might affect the outcome variables not only through the technology adoption. For example, farmer education may affect yield through adoption of a given technology and through overall crop management. Some of the estimates that use aggregate values from the locality as instruments could be affected by the reflection problem (Manski, 1993). Such criticism on selection of certain variables as instruments is not unique to any particular crop or technology. Many researchers argue that with perfect instruments being difficult if not impossible to find, causality is near-impossible to establish. A number of studies have deployed “less perfect” methods (e.g., propensity score matching, which control for observed heterogeneity) to estimate the impact of technologies.

Finally, one of the most popular practices to address endogeneity of adoption in its binary form and heterogeneity of impacts is endogenous switching regression (ESR). The ESR model allows the technology choices to interact both with observable variables and with unobserved heterogeneity, by estimating separate regressions for adopters and non-adopters. The other advantage of the ESR over other methods such as propensity score matching is that it enables the construction of a counterfactual based on returns to characteristics of adopters and non-adopters. The ESR framework was used to assess the impact of maize technologies by Kassie et al. (2018), Ng’ombe et al. (2017), Wossen et al. (2017), Abdulai (2016), Jaleta et al. (2016) among many others (Table 2). Similar to the two-stage least squares or control function approach, selection instruments are required in ESR framework for the model to be identified. Di Falco et al. (2011) suggested that admissibility of these instruments can be examined by performing a simple falsification test: if a variable is a valid selection instrument, it will affect adoption (the selection decision) but not outcome among those who did not adopt. Unfortunately, many of the studies that used ESR did not explain the variable selection or admissibility of the variables. For example, Kassie et al., (2018) did not indicate anywhere in the paper that they used distance from farmer household to input distribution center and agricultural information offices as selection instruments. A close examination of supplementary information provided in the on-line documents is required to obtain this key information. On the other hand, studies like Wossen et al. (2017) and Jaleta et al. (2016) clearly indicated the instruments used in their studies, but they did not conduct any statistical test or systematically argue in support of their choice of instrument. The criticisms with respect to the selection of instruments for the two-stage least squares and control function approaches – especially the possible inadequacy to meet the exclusion restriction – are applicable here also. Given the instrumental variable is valid, the most important advantage of employing the ESR framework is that we can address the heterogeneity of impacts of technology adoption explicitly. The impact heterogeneity that emerges from the differences in policy, institutional, and agro-ecological factors has not been adequately addressed in maize production systems. A more detailed discussion is given below.

Heterogeneity and relevance of the context. Most of the impact studies in maize systems focus on the mean effect of intervention, irrespective of the identification strategy. However, the effect of agricultural growth on poverty depends on inequality in the distribution of resources, especially land (Thirtle et al., 2003). For example, a recent study in maize agri-food systems conducted by Zeng et al. (2018) indicated that land rental markets can potentially enhance household welfare by increasing crop variety adoption in Ethiopia. Depending on the institutional and agro-climatic conditions,

(continued on p. 15)

[2] Awondo et al. (2017) used four instruments to address endogeneity of production variables (distance to the nearest school in kilometers, time taken to walk to the school in minutes, distance to the place where health treatment was sought for in kilometers, and how long it took to travel to the nearest major road). Arslan et al. (2017) used instrumental variable estimation of the fixed-effects and first-differences panel data models with possibly endogenous regressors. To find instruments, they exploited “the key role played by social learning” in the adoption of agricultural practices (e.g., average neighbors’ adoption of a given technology) and the number of years that the household’s head has lived in the village. Burke et al. (2017) used fertilizer prices, distance to town, distance to a fertilizer retailer, and the education level of the household head as instruments to model fertilizer use and its interaction variables. Zeng et al. (2017) used three instruments to estimate impacts of improved varieties. They were distance to the nearest maize seed dealer from the farmer’s home, number of years the farmer has been aware of the improved variety, and elicited binary indicator of the existence of temporary disruption in maize seed supply during the sowing month of the cropping season. Mathenge et al. (2014) used the ratio of village median farm-gate seed price to village median farm-gate grain price, the cumulative adoption rate estimated from the sample at the location scale as instrumental variables.

[3] To model the impact of drought tolerant varieties, farmer experience of drought and heat stress in the past five years was used as the instrument by Lunduka et al. (2017) and a dummy variable for households having nonagricultural business income by Holden and Fisher (2015). Smale and Mason (2014) used cumulative adoption rate in the district, measured as the percentage of smallholder maize area that is planted to F1 hybrids in the previous season as the instrumental variable. This variable was constructed from secondary data. Mason and Smale (2013) used a dummy variable that controls for whether or not the household head is related to the village headman or chief as the instrument variable to address endogeneity in impact model of subsidized seeds in Zambia. As a rationale behind the instrument selection, the authors indicated that the traditional authorities contribute informally to the identification and approval of subsidy beneficiaries.

Table 2. Technology impact studies in maize production systems (2008-2017).

Study	Country	Sample size	Technologies	Key dependent variable(s)	Identification strategy
Abdulai and Abdulai (2017)	Zambia	372	conservation agriculture	environmental efficiency	selectivity-corrected meta-frontier approach
Arslan et al. (2017)	Tanzania	977	sustainable intensification practices	grain yield	fixed-effects instrumental variable
Awondo et al. (2017)	Uganda	516	improved varieties	risk (variability in crop revenue)	instrumental variables
Burke et al. (2017)	Zambia	7,127	inorganic fertilizers	grain yield	correlated random effects estimator and instrumental variables
Chepchirchir et al. (2017)	Uganda	560	push-pull (habitat management strategy)	grain yield, household income, poverty and per capita food consumption	generalized propensity score matching
Kassie et al. (2018)	Ethiopia	2,132	combination of improved varieties, inorganic fertilizers and diversification	grain yield, and production cost	panel data endogenous switching regression models
Kotu et al. (2017)	Ghana	2,545	sustainable intensification practices	grain yield, and net income	semi-parametric treatment-effects model
Koussoubé and Nauges (2017)	Burkina Faso	4,481	inorganic fertilizers	grain yield	fixed-effects, 3-stage least squares
Lunduka et al. (2017)	Zimbabwe	200	drought-tolerant varieties	grain yield	control function approach
Makate et al. (2017a)	Zambia, Malawi, Mozambique	312	sustainable intensification practices	grain yield, crop income, and food adequacy	conditional maximum likelihood approach
Makate et al. (2017b)	Zimbabwe	601	drought-tolerant varieties	grain yield, grain sold, and consumption	propensity score matching
Ng'ombe et al. (2017)	Zambia	7,512	conservation agriculture (combination of technologies)	net revenue	multinomial endogenous switching regression
Wainaina et al. (2017)	Kenya	1,344	sustainable intensification practices	household and per capita income	propensity score matching
Wossen et al. (2017)	Nigeria	2,084	drought-tolerant varieties	grain yield and risk (variability)	endogenous switching regression
Zeng et al. (2017)	Ethiopia	791	improved varieties	child nutrition	instrumental variables
Abdulai (2016)	Zambia	408	conservation agriculture	grain yield, throughput accounting ratio, and poverty indices (headcount, gap, severity)	endogenous switching regression
Haile et al. (2016)	Malawi	1149	sustainable agriculture practices	grain yield, and value of harvest	efficient influence function and propensity score matching
Jaleta et al. (2016)	Ethiopia	290	minimum tillage	grain yield, labor use, and net income	endogenous switching regression
Magrini and Vigani (2016)	Tanzania	1,543	improved seeds and inorganic fertilizers	food security (food availability, access, utilization, and stability)	propensity score matching
Manda et al. (2016a)	Zambia	800	sustainable intensification practices	grain yield and household income	multinomial treatment-effects model
Manda et al. (2016b)	Zambia	810	improved varieties	child nutrition	endogenous switching regression, and propensity score matching
Mutenje et al. (2016)	Malawi	892	improved varieties, storage, soil and water management	grain yield	none
Pettersson and Wikström (2016)	Mali	150	human fertilizer	grain yield	propensity score matching
Coromaldi et al. (2015)	Uganda	2,124	improved varieties	net revenue, per capita food consumption, on farm crop diversity	endogenous switching regression
Holden and Fisher (2015)	Malawi	350	drought-tolerant varieties	grain yield	household fixed-effects, control function
Kassie et al. (2015b)	Malawi	1,925	sustainable intensification practices	grain yield and risk exposure (skewness)	endogenous switching regression
Khonje et al. (2015)	Zambia	810	improved varieties	crop incomes, consumption expenditure, poverty, and food security	endogenous switching regression, and propensity score matching

Study	Country	Sample size	Technologies	Key dependent variable(s)	Identification strategy
Zeng et al. (2015)	Ethiopia	1,396	improved varieties	grain yield, production cost, poverty	instrumental variables
Bezu et al. (2014)	Malawi	1,375	improved varieties	per capita household income, assets, own maize consumption	control function approach and instrumental variables
Kassie et al. (2014)	Tanzania	680	improved varieties	food security	generalized propensity score matching
Mathenge et al. (2014)	Kenya	1,578	improved varieties (hybrids)	household income, assets, poverty, inequality (relative deprivation)	instrumental variables, household fixed-effects
Ndlovu et al. (2014)	Zimbabwe	470	conservation agriculture	grain yield (productivity) and technical efficiency	Heckman's sample selection model
Smale and Mason (2014)	Zambia	3,231	improved varieties (hybrids)	household income, poverty, assets (including farm equipment and livestock)	control function/ instrumental variables, and household-level fixed-effects
Gitonga et al. (2013)	Kenya	1,340	metal silos	storage loss, cost and duration of storage, and food security	propensity score matching
Mason and Smale (2013)	Zambia	3,231	improved varieties (hybrids)	grain yield, household income, poverty, inequality (relative deprivation)	control function, and household-level fixed-effects
Sheahan et al. (2013)	Kenya	906	inorganic fertilizers (nitrogen)	grain yield	Mundlak–chamberlain approach
Amare et al. (2012)	Tanzania	613	cropping system (maize and legume)	income and consumption expenditure per capita	propensity score matching
Cunguara and Darnhofer (2011)	Mozambique	6,149	improved seeds, tractor mechanization, animal traction, improved granary	household income	propensity score matching
Becerril and Abdulai (2010)	Mexico	325	improved varieties	per capita consumption expenditure, and poverty	propensity score matching

the 'treatment effect' of interventions will be different for different groups of farm households. A better understanding of impact heterogeneity is essential for designing scaling out strategies that can help avoid the widening income inequality while promoting more profitable and sustainable production practices in maize systems. Some studies addressed potential impact heterogeneity by including interaction terms of farm and household characteristics with technology variable in the regression equation on outcome (e.g., Awondo et al., 2017). However, a clear examination of heterogeneity might require inclusion of a number of interaction terms, which would in turn demand more instrumental variables to identify the equation. A more systematized and pragmatic procedure would be the estimation of ESR model. Nevertheless, many studies that used ESR framework restricted themselves to average effects, and did not explore the possible impact heterogeneity. For example, although Abdulai (2016), Wossen et al. (2017), Khonje et al. (2015), Jaleta et al. (2016) and many others explored technology impacts using ESR in multiple dimensions (in terms of grain yield, per capita expenditure, poverty, food security etc.), they did not hypothesize that the impact would be different in different socio-economic groups.

Why is it important to estimate the differential technology impact? Discrimination based on group attributes such as ethnicity and gender has long attracted the attention of economists (Alesina et al., 1999; Jurajda, 2005; Banerjee et al., 2005a). In the field of political economy, social divisions undermining economic progress form one of the most relevant research hypotheses (Banerjee et al., 2005b). On the empirical side, however, there exists only limited evidence for social segregation shaping agrarian change and rural development. Not many studies focused on the inclusion dimension, with a possible exception of gender. Gender is shown frequently as one of the most important elements of social segregation.[4] However it is not the only factor. In South Asia, for example, the existing caste system causes differential farmer access to the factors of production and therefore could generate only lower crop income (Anderson, 2011; Kumar, 2013; Birthal et al., 2015). The MAIZE researchers may cover the livelihood impacts of technological interventions recognizing the relevance of social segregation and discrimination and estimate the technology impacts separately for different socially and economically disadvantaged farmer groups.

[4] Although women contribute critically to the food production, they face discrimination in terms of access to production resources and increased constraints in agricultural production than men Theriault et al. (2017a); WB, FAO, & IFAD (2008). Studies like Fisher and Carr (2015) and Ndiritu et al. (2014) analyzed data from gender-disaggregated household surveys to examine how gendered roles and responsibilities influence uptake of maize technologies. Nevertheless, there are not many research attempts at the impact side.

6. Impact evaluation in MAIZE: Challenges and opportunities

Similar to the adoption studies, there is an abundance of technology impact studies in maize systems, especially when we compare the literature on other crops. While **many of the impact studies in maize agri-food systems display commendable scholarship to establish causality of technology adoption** in maize production systems in developing countries, **more research is required in certain specified topics.** Alongside diversifying the study area, future MAIZE impact studies could focus on increasing the rigor of impact evaluation.

- The impact assessment in maize has been **short-term**, done mostly in the context of ongoing R4D projects. The Stripe panel indicated that while there is a proliferation with respect to the number of ex-post impact assessments, the methodology is rather “weak and being conducted on small projects (rather than programs) too soon after termination” (CGIAR Science Council, 2009, p. vi). This situation has remained unchanged over time, possibly due to the persistent desire of the donors to document and report the effective use of funds back to their constituencies. This has not only resulted in weak impact studies, but also inability to capture impacts beyond certain biophysical indicators like yield. We have elaborated this challenge as the next point.

- The literature review shown in Table 2 indicates that a diverse set of metrics have been used to measure the impacts of maize technology adoption in farmers’ fields. Changes in the grain yield is relatively easier to measure than other metrics in the farm-household surveys, and yield changes form an integral component of most of the MAIZE impact targets (CRP MAIZE, 2016). Another important impact metric in this regard is yield variability, as one of the main objectives of MAIZE is reducing the frequency of production shortfalls. Finally, **the livelihood impacts of maize technologies require increased research focus.** Although MAIZE does not specify any of its impact targets in terms of changes in farmer livelihood or welfare status, the program activities targets the areas with the highest poverty concentrations. Furthermore, yield increase may not always result in welfare enhancement of farm households, especially when they face a volatile output market. A recommendation to include the livelihood indicators in impact assessment, nevertheless, demands significant changes in planning and executing field surveys. This is because the livelihood impacts of technology interventions in agriculture often appear in the farm-household dataset after a lag of many years. This is a major challenge for MAIZE as most of the third-party funded projects last only for 3-4 years. To capture the impact of intervention in poverty, food security, and nutrition, we require more panel datasets.

- Most of these **studies have not addressed system-level impacts and impact pathways.** Conceiving agricultural development as a complex social process in which people seek solutions to their problems, often by reinventing new opportunities offered by the technologies according to their own production systems (Douthwaite et al., 2003). This process involves a high degree of non-linearity, which is ignored by the current ‘best practice’ economic evaluation methods used in the literature. Also the potential role played by institutional innovations and policies that ensure farmer access to information and inputs and reliable markets for selling surplus products are largely overlooked.

- There is a **strong regional bias in impact studies toward sub-Saharan Africa** and there is hardly any evidence on the technology impacts in maize production systems of South or Southeast Asia. As the pace of technology advancement in these regions is not slow (Dar et al., 2016), the observed dearth of socioeconomic studies can only be explained by a severe lack of research funding for the research in this discipline as such.

- Similar to the case of adoption studies, **new data collection methods** like satellite imageries and use of unmanned aerial vehicles (UAVs) could be effectively employed in impact assessment. Poverty and economic wellbeing status of households were estimated through remote sensing by Jean et al. (2016). In addition, meso-level data on seasonal vegetation indices (e.g., Normalized Difference Vegetation Index, Canopy Greenness Index etc. from Moderate Resolution Image Spectroradiometer or MODIS) and abiotic stresses (precipitation, evaporative stress etc.) from the previous year of the survey are hypothesized to predict poverty and food security status of rural households. Another set of data can be availed from higher resolution satellites like Landsat 8, which can help detect crop growth anomalies (e.g., crop diseases, drought), and land use indicators (e.g., timing of planting, area planted, crop rotation cycles, field size distribution etc.) (Matton et al., 2015; Burke and Lobell, 2017).

7. Way forward

Over the last four decades, CGIAR research interventions in genetic improvement, pest management, and natural resource management have generated significant economic benefits, considering the investments made (Renkow and Byerlee, 2010). Institutionalizing the impact assessment has become a priority to address underinvestment in CGIAR R4D. MAIZE has developed this strategy, to advance practical understanding about the challenges faced by smallholder farmers to access the technologies and to benefit from them. This strategy should also help practitioners frame effective and inclusive scaling out strategies in developing countries. Examining the existing review of literature in maize over the last one-decade and the advancements made in the field, we have come up with the following ten strategic research ideas for MAIZE adoption-impact studies.

1. ***Documenting the R4D impacts rigorously and objectively.*** A study is being conducted to document the global use and effects of improved maize **germplasm** through systematically collecting the details on release of varieties, estimating the adoption rate and economic benefits from adoption, and attribute the technology. **Similar effort is required to document the R4D in the field of sustainable intensification.**

2. ***More precise data on varietal use by farmers.*** Standardization of DNA fingerprinting technique in maize for more precise characterization of germplasm in the farmers' field.

3. ***More explicit understanding of gender and intra-household decision-making.*** Most of the existing adoption/ impact studies capture gender dimension with a dummy variable on sex of the household head, and by doing so, they overlook the roles women play in decision-making and providing labor in maize systems.

4. ***Enhancing the methodological rigor of impact assessments.*** Employing rigorous econometric methods and randomized trials will be employed to (a) establish causation and (b) explicitly accounting the socioeconomic and institutional heterogeneity.

5. ***Greater geographical reach****.* While retaining the pace of socioeconomic research in sub-Saharan Africa, **more research needs to be conducted in the maize agri-food systems of South and Southeast Asia and Latin America.** The role of maize would be different in systems, in which the grains are produced primarily for the market and not for subsistence consumption. Targeted search for research funds will be the first step toward this goal.

6. ***Coordinating research across borders.*** Cross-country comparisons are possible by unifying parts of survey questionnaires in different field activities conducted by MAIZE researchers. In particular, recommendations will be given to the scientists to include a set of generic variables that stand proxy for improvements in human welfare (e.g., Food Insecurity Experience Scale).

7. ***Effectively using the existing data.*** Meta-analyses using the existing vast literature to look at different dimensions – for example, inclusion of poor in the technology dissemination programs, adoption and impacts of climate change mitigation technologies etc. – would provide valuable insights on agrarian development pathways. Existence of diverse impact matrices is one of the major challenges to conducting meta-analysis, which can be overcome by setting up a common set of impact parameters across different surveys conducted within MAIZE. There is an opportunity for collaboration with other Agri-Food CRPs and SPIA.

8. ***New rich data sources.*** The conventional household surveys can be complemented with nonconventional methods of data collection like satellite imageries and use of UAVs. Developing a technical report on the potential of employing satellite imageries and UAVs for adoption-impact studies will be the first step toward it. Use of these non-conventional methods of data collection could be complementing the household surveys in some of the forthcoming research projects. Together for MAIZE and WHEAT, a research protocol will be developed on scope of the novel data collection methods and strategies for adoption-impact studies. There is an opportunity for collaboration with other Agri-Food CRPs and SPIA.

9. ***Establishing long-term data collection activities.*** In the key MAIZE intervention areas and expansion frontiers, panel surveys can be conducted for data needed for rigorous assessment of technology diffusion patterns, impact pathways, and spillovers. This exercise would require secure continued support. There is an opportunity for collaboration with other Agri-Food CRPs and SPIA.

10. ***Facilitate the learning experience.*** This can be achieved by complementing the conventional quantitative studies with qualitative ones, especially to identify the patterns of technology dissemination in the society and the associated impact pathways. Qualitative studies and participatory approaches are important tools to provide effective feedback to the R4D system, so that the scaling out mechanisms can easily adapt to deliver technologies more efficiently in complex farming systems.

11. ***Capacity building.*** Scientist and student training programs to impart more analytical rigor in adoption and impact analysis and for capacity building across CRPs MAIZE and WHEAT.

The current body of literature reviewed has variously relied on fragmented donor funding. For MAIZE it is critical to secure the resources needed to properly implement this adoption and impact strategy and operationalize the above ten ideas. By systematically addressing these priorities we will fill the gaps between the various fragmented studies and in the end, adequately document the achievements of the CGIAR Research Program on MAIZE.

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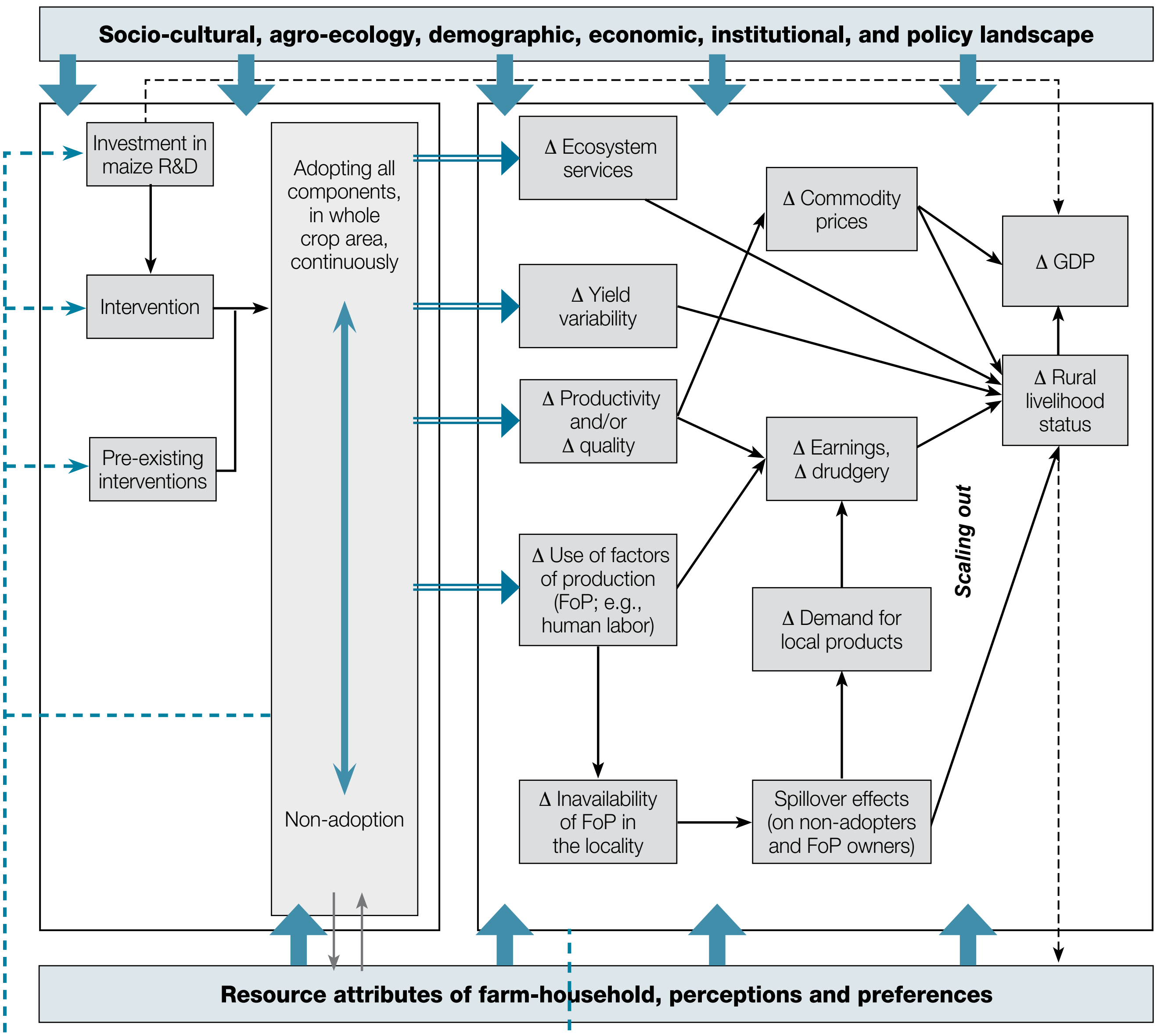
Appendix 1. Framework of adoption-impact studies



The CGIAR Research Program on Maize (MAIZE)
Email: maizecrp@cgiar.org • Web: http://maize.org

International Maize and Wheat Improvement Center (CIMMYT)
Apdo. Postal 041
C.A.P. Plaza Galerías, Col. Verónica Anzures
11305 CDMX, MÉXICO
Tel: +52 (55) 5804 2004
Email: cimmyt@cgiar.org
www.cimmyt.org

International Institute of Tropical Agriculture (IITA)
Headquarters, PMB 5320, Oyo Road, Ibadan 200001
Oyo State, Nigeria
Tel: +234 700800IITA, +1 201 6336094
08034035281, 08034035282, 08034035283
Fax: +44 208 7113786
Email: iita@cgiar.org
www.iita.org