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IFPRI Discussion Paper 02199

September 2023

Adoption and Impacts of Agricultural Technologies and Sustainable Natural Resource Management Practices in Fragile and Conflict Affected Settings

A Review and Meta-analysis

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Abstract

Climate change and conflicts co-exist in many countries with significant welfare and socio-environmental implications. Different approaches are being promoted to adapt and build resilience to these fragilities including the adoption of sustainable farm practices that have the potential to increase agricultural productivity and maintain environmental sustainability. We undertake a systematic review and perform a meta-analysis to understand and synthesize the adoption and impacts of agricultural technologies and natural resource management practices with a special attention to fragile and conflict affected settings. We employ state of the art machine learning methods to enable process and selection of appropriate papers from a universe of over 78,000 papers from leading academic databases. We find that studies on adoption and impact of agricultural technologies and natural resource management practices are highly clustered around Ethiopia and Nigeria. We do not find any studies on Small Island States. We observe a wide array of characteristics that influence adoption of these technologies. Of the over 1400 estimates of determinants collected, majority predict input technologies while very few studies and estimates are found in relation to risk management and mechanisation technologies. Our meta-analysis shows an average effect size of 7 - 9% for the different technologies and practices. For the outcomes: land productivity, food security and household welfare, we obtain effect sizes of 6, 8 and 9% respectively. We do not observe much in terms of publication bias. Both climate and conflict vulnerability not only cause far more food insecurity, poverty, and degradation of the environment on their own but also reinforce each other through the climate change – conflict linkage. For these detrimental effects to be curtailed, utilisation of climate-smart agricultural technologies and natural resource management practices need to be encouraged. We thus lend credence to the development, dissemination and upscaling of these sustainable practices. We observe a lot of space for growth and adoption of these technologies.

Acknowledgements

This work was undertaken as part of the CGIAR Research Initiative on Fragility to Resilience in Central and West Asia and North Africa. The CGIAR Initiative on Fragility to Resilience in Central and West Asia and North Africa (F2R-CWANA) is building resilient agrifood systems that can withstand the impact of climate change, generate economic opportunities, and deliver better incomes and livelihoods for rural communities in the region. Other CGIAR centres participating in initiative include the International Center for Agricultural Research in the Dry Areas (ICARDA), Alliance of Bioversity and CIAT and the International Water Management Institute (IWMI). We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: https://www.cgiar.org/funders/

1. Introduction

Increasing agricultural productivity and maintaining environmental sustainability are two important and seemingly complementary sustainable development goals (Bennett, 2017; Cassman & Grassini, 2020). However, potential trade-offs could exist in some smallholder farming systems where agricultural production could adversely affect the environment and vice versa (Barrios et al., 2008; Cohn et al., 2017; Tahmasebi et al., 2018). A case in point is climate change which critically affects agricultural production and productivity but is also exacerbated by unsustainable agricultural production practices associated with the release of greenhouse gases (Lobell et al., 2011; Ortiz-Bobea et al., 2021; Qiao et al., 2022). In sub-Saharan Africa, the growth rate of the population is accelerating at an unprecedented rate. However, the region's arable land, water resources, and agricultural infrastructure are limited (Filho et al., 2022). As a result, many of the region's crops are grown on small farms using traditional agricultural practices requiring substantial quantities of energy, land, and water (Deininger et al., 2017). This makes it difficult for farmers to provide sufficient food for the growing population while preserving the environment (Bjornlund et al., 2020). The adoption of natural resource management practices which include different aspects of climate-smart agriculture, sustainable intensification, conservation agriculture, agroforestry and carbon farming has been argued to offer these twin productivity and environmental sustainability goals (Lipper et al., 2014; Tabe-Ojong et al., 2023a; Tabe-Ojong et al., 2023b).

However, the adoption of these natural resource management practices has been extremely low and varying in many developing countries (Duflo et al., 2008; Emerick et al., 2016; Sheahan & Barrett, 2017). Missing markets, market imperfections, productivity and supply-side constraints have been identified as some of the constraints limiting the adoption of some of these CSA practices (Ashraf et al., 2009; Hanna et al., 2014; Suri, 2011). Lack of profitability including heterogeneous profits with some farmers benefiting more than others also matters (Suri, 2011). Also, poor rural infrastructure may lead to increased transaction costs, lowering adoption (Suri, 2011). Lack of adequate and timely information, education, and training has been attributed as some of the factors constraining the adoption of these practices among smallholder farmers (Kabunga et al., 2012; Tabe-Ojong, 2022; Tabe-Ojong et al., 2023c). Some reviews have been undertaken to synthesise the evidence of these practices and their impacts as a way of improving learning on the adoption (Acevedo et al., 2020; Piñeiro et al., 2020; Suri & Udry, 2022). While these reviews are extensive and improve our understanding on technology adoption, there exist knowledge gaps in focus and context especially with regards to geographical coverage. Moreover, none of them looks at conflicts and fragility as possible intermediaries on the agricultural technology adoption path.

Given this, we use a machine learning and human aided review to investigate the determinants of adoption and or dis-adoption of a range of agricultural technologies and sustainable natural resource management practices in fragile and conflict-affected settings by highlighting barriers and enablers of adoption. Our definition of agricultural technologies constitutes new methods and practices which are introduced to farmers either externally (from an external source/ provider) or internally (from farmers' own local expertise and processes), aimed at improving agricultural outcomes and sustainability of the agricultural production system. We also examine the productivity, welfare, and environmental implications of the adoption of these agricultural technologies and natural resource management practices.

Our review includes technologies and natural resource management practices based on six categories: improved seeds, chemical inputs, natural soil fertility technologies, erosion management techniques, mechanisation, and risk reduction technologies. As such, it builds on existing reviews and contributes to the broad literature on the adoption of natural resource management practices in several ways. First, we focus primarily on fragile and conflict-affected settings around the world. Fragility is defined by the World Bank as a systemic condition or situation characterized by an extremely low level of institutional and governance capacity which significantly impedes the state's ability to function effectively, maintain peace and foster economic and social development (World Bank, 2022). To this end, fragility might emanate from political and non-political situations including those related to climate stress. Thus, several Small Island States are some of the most vulnerable (Scandurra et al., 2018) and continually classified as such (World Bank, 2022). Conflict is defined by the World Bank as a situation of acute insecurity driven by the use of deadly force by a group, including state forces, organized non-state groups, or other irregular entities, with a political purpose or motivation (World Bank, 2022). Both dimensions of fragility might coexist, for instance in several Sahelian/West African countries which have faced both dimension of fragility in the last several decades (Benjaminsen, 2016; Raleigh, 2010). Focusing on these geographical areas is important and timely as these countries are likely more exposed to higher risk of food insecurity and other adverse welfare conditions (IFPRI, 2023; Nnaji et al., 2023; Sanch-maritan & Vedrine, 2019).

This review is the first to tackle the adoption question or the implications of technology adoption. From an adoption perspective, a number of studies are of note (Table S1). Piñeiro et al. (2020) review the uptake of sustainable agricultural practices, and Acevedo et al. (2020) review the adoption of climate resilient crops by small-scale farmers in low and middle-income countries. Ahmad et al. (2020) also documents soil erosion control practices in Asia while Stathers et al. (2020) look at technologies for the reduction of postharvest losses. More recently, Arslan et al. (2022) and Ruzzante et al. (2021) conduct meta-analyses of the determinants of technology adoption. Oyetunde-Usman (2022) focused more on land attributes, gender and social learning as key drivers of adoption in their study of East and West Africa. Schulz and Börner (2023) show that where land, capital and technology know-how are key ingredients in utilising a technology, their uptake increase and attenuate when these factors are abundantly available. Suri and Udry (2022) provide an expert review of agriculture technology adoption in sub-Saharan Africa with a development and agricultural economics lens. From an impact perspective, one study of note is Takahashi et al. (2020) who provide an expert and scoping level assessment of impacts with a focus on sub-Saharan Africa. As such, we contribute to the growing work in agricultural and climate related economic studies assessing the value additional impact of adoption of technological advancements and their consequential influence on agricultural productivity and well-being of farmers. These studies vary in interest, methods, and contributions, thus leaving unanswered questions. Table S1 in the supplementary material summarises these reviews in their thematic, methodological and outcome focus and whether the studies implemented systematic search and review process or not.

As can be seen from Table S1, most of the studies assess general determinants however Acevedo et al. (2020) look at the uptake of climate resilient crops, Ahmad et al. (2020) look at erosion control practices and Stathers et al. (2020) examine post-harvest handling technologies. A number of studies conduct meta-analysis regressions to assess the effect of different determinants (Arslan et al., 2022; Ruzzante et al., 2021; Schulz & Börner, 2023; Stathers et al., 2020) and Acevedo et al. (2020) and Piñeiro et al. (2020) are scoping reviews. Only one study (Takahashi et al., 2020) look at some component of impact using an expert analysis of the content and not through meta regressions of impacts.

One key addition that this study contributes is the conflict and vulnerability angle. Indeed, there is a potential black hole scenario of technology adoption and impact regarding "farmers in crises", where household welfare and poverty are affected by conflicts, climate shocks or both (De Jalón et al., 2016; Sanch-maritan & Vedrine, 2019) yet, these effects are not well synthesized in meta analyses. From this dimension, this review therefore adds value in two ways. First, it focuses primarily on fragile and conflict-affected settings around the world. Fragile settings in this case refer to locations (countries) induced into fragility due to political unrest and internal governance weakness while other dimensions of fragility can emanate from long term climatic stress such as those faced by Small Island States and the Sahel countries. There is a special need to focus on these countries as they are more exposed to higher risk of food insecurity and to a certain extent humanitarian crisis.

Secondly, through a meta-analysis, this review attempts to document the causal relationships between the use of these farm practices with productivity, welfare, and environmental sustainability outcomes at farm level. Several existing reviews on technology adoption and natural resource management are quite general in nature and hence mainly scoping reviews. While the strength of scoping reviews lies in the breadth of the scope and size of the material reviewed, one key weakness is their lack of causal learning (Grant & Booth, 2009). The limitations in causal learning stem from the methodologies of scoping reviews, which broadly aim to understand the existing relationship and not specifically those that establish causal relationships. Systematic meta-analysis is therefore the most preferred analytical strategy for causal learning in literature review as they synthesize already studies of tested methodologies and account for all the methodological and design differences to prove a measure of the overall effect size. Besides this attention to causal learning through meta-analysis, this review is more comprehensive in the scope of technologies considered, far beyond previous studies that are more limited in scope regarding the types of technologies studied (for instance only post-harvest technologies (Stathers et al., 2020) or only erosion management technologies (Ahmad et al., 2020)). In our case, the aspect of coverage and scope also becomes glaring as we consider a large set of studies on agricultural technologies and natural resource management including improved seeds, chemical inputs, natural soil fertility technologies, erosion management techniques, mechanisation, and risk reduction technologies. Apart from our specific geographical coverage, our review is closely related Ruzzante et al (2021), and yet it does much more by conducting impact meta-analyses not conducted in the latter.

One other key contribution is a methodological one where we rely on machine learning in the literature search. In recent years, machine learning tools and instruments that aid efficient literature search strategies have been suggested by researchers (van de Schoot et al., 2021).

Given the expanse of the literature that we review and the desire for precision in identifying the right studies that meet the exact review criteria, human and hand-aided selection process are excruciating, more error-prone, and less efficient compared to a machine-learning-aided selection process. Moreover, with machine learning-aided literature selection, methodical transparency is assured, making for easy replicability by researchers and other development actors (van de Schoot et al., 2021; Van Dijk et al., 2023). This is important as it ensures scientific continuity and effective follow up. Of the studies in Table 1 above, three of them (Piñeiro et al., 2020; Schulz and Börner, 2023; Stathers et al., 2020) have used machine learning in the literature selection process. However, all of them assess few papers, potentially implying that they might be limited in scope and their depth of the search process. In this review, we robustly assess over 78,000 papers resulting in a selection of 132 papers on determinants and 42 papers on impacts.

2. Methodology

2.1. Thematic scope of the review.

We consider agricultural technologies and natural resource management practices under six key dimensions: improved seeds, chemical inputs, natural soil fertility technologies, erosion management techniques; mechanisation, and risk reduction technologies. The first category of improved seeds includes climate-resilient seeds, pest resistant seeds, drought resistant seeds and genetically modified seeds. The second category includes chemical inputs such as chemical fertilisers, pesticides, herbicides that are important as both productive and defensive inputs which are geared at increasing agricultural productivity. The fourth category broadly captures technologies and practices that improve soil fertility management. Technologies assessed here are both natural soil fertility technologies such as mulching, organic fertiliser use, crop residue use, inter-cropping, and agro-forestry. The fourth type of technologies include erosion management techniques including conservation farming, soil bunds, contour ploughing, rock bunds and tillage. These technologies and practices broadly include those aimed at controlling the flow of water, maintaining soil stability, controlling sedimentation as well as managing and maintaining optimal watershed. The fifth category refers to mechanisation technologies that include the introduction of new and advanced equipment in farm activities such tractor use, irrigation, treadle pumps, precision farming, water storage and water harvesting, improved grain drying techniques, among others. The final category includes risk reduction technologies which encompasses aspects of agricultural insurance. All the different practices and technologies offer distinct functions that overlap but are generally geared at increasing agricultural productivity and maintaining environmental sustainability.

2.2. Geographical scope

Given our interest in fragile and conflict affected settings, we limit the geographical coverage to only fragile and conflict affected (FCA) countries. Our definition of FCA countries is based on the World Bank's classification (Corral et al., 2020; World Bank, 2022). As such, FCA countries are defined as (1) facing high intensity conflicts defined as those with more than 10 per 100,000 individuals dying in conflict (ACLED data) and more than 10 per 100,000 conflict deaths (UCDP Uppsala data) and more than 250 deaths and more than 150 deaths as per ACLED and UCDP data, respectively; (2) facing medium intensity conflicts; and (3) those with a minimum Country Policy and Institutional Assessment (CPIA) score of 3 or the presence of non-international UN peacekeeping operation or countries from which more than 2000 per 100,000 individuals are refugees

From the above classifications, we used the World Bank list of FCA countries covering 2006 to 2022, excluding Ukraine. While Ukraine has been in conflict since 2014, it was never on the list of FCA countries before 2022. In terms of population, we are interested in smallholders or small-scale farmers and our review includes studies conducted and published between 2000 and 2023 in English language.

2.3. Types of studies

In line with our objectives to assess both the roots and power of agricultural technologies and natural resource management practices, we include two types of studies. The first group includes all quantitative studies that address and examine the determinants of technology adoption and natural resource management. The selected studies include both cross-sectional and panel studies on the impacts of agricultural technologies and natural resource management practices. The impacts here refer to different outcomes such as productivity, welfare and environmental sustainability which were all defined in our pre-registered protocol. Since the aim of this second objective is more causal oriented, we include studies that attempt to establish a causal relationship. We therefore selected studies that were either randomised controlled experiments or those that used quasi experimental methods including difference in differences, instrumental variables, regression discontinuity designs and propensity score matching estimators or panel data with fixed effects. We consider studies that clearly indicated a treatment and a comparison group. A comparison group was defined as a group of farm households not having been exposed to any treatment (technology) within a given study. We select studies that include at least one of the agricultural technologies and natural resource management practices. Of course, some of these technologies are usually bundled (Tabe-Ojong et al., 2023a).

Given our interest in examining experimental and quasi-experimental studies, we assess and account for the level of bias in literature. The conventional ways of assessing bias in systematic reviews including for instance checking the protocol or if a pre-analysis plan of an RCT was previously published (Shamseer et al., 2015). However, we did not envisage to find many studies fulfilling this criterion. We did not exclude any studies based on a bias marker during the selection stage.

Our main search terms were mainly from Rosenstock et al. (2015), which have also been used in other previous reviews such as Arslan et al. (2022). However, we included a few more other search terms from hand picking based on other reviews. We use the conventional Boolean operators to combine themes, and terms to refine the search strategy.

2.4. Data search and selection

From the initial search process from Web of Science and Scopus we extracted 42,024 records for on topics of adoption and 35,960 records on topics of impact. To process all these data, we employed a machine learning driving process to ease selection process. Machine learning is increasingly used in literature reviews and makes the process of literature selection faster, transparent, and easily replicable (van de Schoot et al., 2021). Specifically, we used ASReview, a Python-based open source and transparent algorithm for literature selection.[1] Our machine learning data selection process was in two stages. First, we combined Scopus and Web of Science results into one sheet. We then run an R-script to remove duplicates. Duplicates include a combination of author-year-title, title, abstract, and digital object identifier (doi). We also removed studies that did not have an abstract. At this stage, we were able to remove 30% of records in adoption and about 36% of the studies on impact.

The second stage machine learning strategy includes a training and analysis process. For each of the categories of the studies, we identified between 20 and 30 studies which met the inclusion criteria. We identified these studies by reading a random set of abstracts to confirm our inclusion strategy as per the protocol. Four reviewers (BHG, ENR, MA, CA) conducted this selection of studies for training. At this stage, we used a majority voting process that a study was classified as a training study if all the reviewers agreed with the decision and a study was not classified as a training study if it received the fewest votes. Studies that were borderline on training decision were re-evaluated by the two senior reviewers (BHG & ENR) for a final decision. Using the training data, we re-run a second-stage ASR review to identify the studies for the human-aided selection. To make the literature selection more efficient, we adopted a data driven multi-stage stop-screening procedure (Boetje & van de Schoot, 2023). Our procedure was as follows. First, from the universe of unique (non-duplicate) papers from the first stage screening, we implemented an inclusion ranking based on the training model. We listed the first 2500 papers according to their ranking. In the second stage, we re-run the inclusion model and selected the first 100 papers in each thematic category, which we then moved to the human-aided screening. One researcher (BHG) conducted the ASR screening and did quality assurance checks with another researcher (ENR).

After the machine learning aided data selection, we moved the 500 studies (100 studies for each technology group) coded as highly relevant to the human aided assessment. At this stage, two reviewers (ENR and MA) read all the abstracts and decided on which abstracts would be moved to the full text review. The researchers agreed on the studies to be included and where there was a disagreement, we discussed with each other and arrived at an inclusion consensus. Of the 500 studies subjected to human-aided assessment, 111 studies were selected. An additional 21 studies were included after manual selection. The reviewers maintained a perception that even when the machine-aided literature selection made the process more efficient, there was still necessity for keen human engagement as some relevant papers could be excluded due to a possible imprecise ranking or an inconclusive training algorithm (van de Schoot et al., 2021; Van Dijk et al., 2023). Altogether, we included 132 studies for the full text review. As our search databases were only of published materials, all studies included were peer reviewed. Figure 1 shows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart showing decision making regarding material selection for the review.

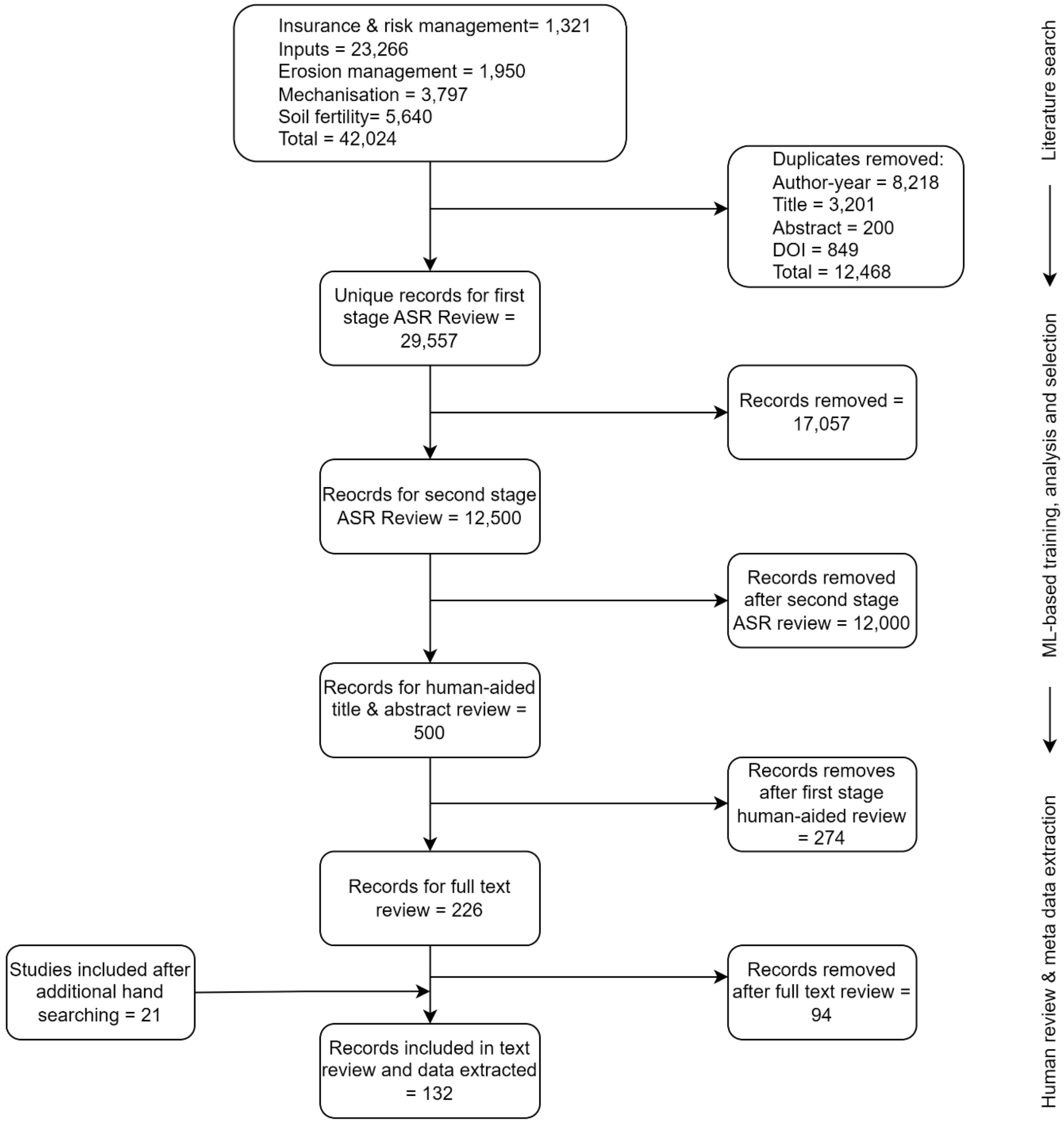
The above process was conducted for both determinants and impacts. Regarding impacts dimension of this review, we included 40 studies in the final review. However, the analysis is based on 28 studies. Two studies were found to be very similar but with slightly different titles published in different journals. We considered this as a form of fraudulent publishing and only

[1] https://asreview.nl/ .

included one study. Five studies did not have standard errors or t-statistics, so they were dropped. Only 28 studies including 156-point estimates were included in the impact assessment.

We then extracted the data using a questionnaire. The questionnaire was created in SurveyCTO and uploaded on the SurveyCTO data collection platform to aggregate the data. The questionnaire captured the following study characteristics: year of publication, number of authors and the study country. Where the study covered multiple countries, each country was entered as an individual study. We further collected the sample size of the studies, whether the study was nationally representative or not. We list the technology under study and its adoption rate. Technologies are categorised into groups as described above. For the adoption dimension of this review, we assessed the results of the studies and extracted all determinants of the technology adoption. For each of the determinants of technology adoption, we extract coefficients, standard errors, significance levels and where available we also pick the confidence intervals of the point estimates. Several studies did not record standard errors. Where alternative statistics (e.g., p-values, t-statistics or z-statistic) were recorded, we collected them and converted them into standard errors using standard conversion formulas (Ruzzante et al., 2021). Altogether, we collect 1400 coefficients from the 132 adoption studies.

Figure 1: PRISMA for Adoption of Climate Smart Agricultural Technologies



2.5. Data Analysis

2.5.1. Assessing determinants of adoption of agricultural technologies

To assess the determinants of technology adoption, first we explored various dimensions of descriptive analysis. As mentioned in the data extraction section, we recode all coefficients that were statistically significant predictors for adoption – whether in the positive or negative dimension. We categorise all the coefficients into 21 groups and summarise their mean effect to assess their contribution to adoption. We use Sankey diagrams to visualise the relationships and the strength of relationship between each of the predictors with the five pre-specified technology groups.

We then used meta-regression, weighted least-square regression that accounts for within-study sampling variance. Following recent studies (Ogundari & Bolarinwa, 2018; Ruzzante et al., 2021), we estimate the partial correlation coefficients of the characteristics for overall technology adoption and for each of the five technology categories. We then used a mixed-effect meta-regression with characteristics determining adoption as a fixed-effect model with a hierarchical structure accounting for with-in-study variations. The mixed effect meta-regression allows us to estimate the true effects due to variability in the observed characteristics and type of technology. The predicted values of the mixed-effect meta-regression can be interpreted as the mean effect size across studies. The empirical form of meta-regression is given as follows:

$$Y_{ij}^{*} = \gamma_{ij} M_{ij} + \varepsilon_{ij} \quad (1)$$

where Y_{ij}^{*} is the estimated expected value of i^{th}predictor variable for the j^{th} technology type, Mij is the vector of moderators (characteristics) and γ_{ij} is the vector of the coefficients and ε_{ij} is the error term. For Y_{ij}^{*}, we estimated the partial correlation coefficient (PCC) using the formula:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \quad (2)$$

The standard error of the PCC is calculated as follows:

$$SE_i = \sqrt{\left(1 - PCC_i^2\right)/df_i} \quad (3)$$

The advantage of using the standard error of the PCC instead of a coefficient estimate is that it standardizes the coefficient across studies. In case of this lack of uniformity in the meta data extracted, the partial correlation coefficient is the preferred method that allows to relative comparison of the strength between variables and an outcome given the presence of other variables (other determinants) (Ogundari & Bolarinwa, 2018; Ruzzante et al., 2021). There are several benefits of using PCCs. First, PCCs are unitless measures and therefore allow partial correlations from multiple different studies to be compared to each other (Stanley & Doucouliagos, 2012). Moreover, partial correlations can be computed from a large set of estimates and studies than other effect size measures and yet the interpretations remain easy and straightforward to understand (Stanley & Doucouliagos, 2012). For its advantages, PCC has been the preferred method for meta-analysis in technology adoption studies (Ogundari & Bolarinwa, 2018; Ruzzante et al., 2021) and overall in other applied disciplines. We used the R package *metafor* (Viechtbauer & Cheung, 2010) to estimate the mean effect size by the characteristics. The weights for the regression are estimated using the formula:

$$W_j = \frac{1}{\left(\hat{\tau}^2 + s_j^2\right)} \quad (4)$$

where s_j^2 is the estimate of the sampling variance σ_j^2 of the j^{th} study and $\hat{\tau}^2$ is an estimate of the inter-study heterogeneity τ^2.

2.5.2. Effects of adopting agricultural technologies

To achieve our objectives of assessing the impacts of agricultural technologies on household welfare, we adopt nuanced approach via targeted research inquiries. We are driven by the desire to be as comprehensive as possible while cognisant of both the limitation in data as well as the biases that might abound in how studies report findings. Investigations based on limited datasets tend to yield estimations of impact that are more susceptible to bias compared to those drawn from more expansive datasets (Sterne & Harbord, 2004). However, through meta-analysis, outcomes from various individual studies can be amalgamated to yield statistically robust estimation of the average effect of closely related but independent studies on given outcomes. For facilitating clear comparison across various effect sizes, standardization is pivotal especially where studies usually measure outcomes in different scales and modes of reporting results. Among the various methods of standardizing effect sizes across different studies, Pearson's correlation coefficient (r), Cohen's d, and the odds ratio (OR) have become prominent (Field & Gillett, 2010).

Cohen's d is predicated on the standardized difference between two means. This involves the subtraction of the mean of one group from that of another, followed by normalization through division by the standard deviation (s). The standard deviation is computed as the summation of squared deviations (i.e., the difference between each data point and the mean, squared) divided by the total number of data points (Cohen, 2013). Calculating the variance typically relies on properties associated with larger sample sizes, although various meta-analysis guidebooks endorse alternative approximations (Lin & Aloe, 2021). However, we follow the widely used where Cohen’s d is given by the formula:

$$d_i = \frac{m_{1i} - m_{2i}}{s_i} \qquad (5)$$

where m_{1i} and m_{2i} are the difference in means between the treated and the control groups. The standard error is then given by the formula:

$$SE(d_i) = \sqrt{\frac{N_i}{n_{1i}n_{2i}} + \frac{d_i^2}{2(N_i - 2)}} \qquad (6)$$

where n_{1i} and n_{2i} are the sub-sample sizes for treated and control groups.

The subsequent phase involves the selection of the appropriate estimation methodology. We use a Random Effects Maximum Likelihood (REML) model to compute the overall effect size (Tanriver-Ayder et al., 2021). The foundation of a Random Effects meta-analysis model is grounded in the premise that effect sizes across studies exhibit variability, with the studies themselves emanating from a random sample extracted from a broader population of research endeavours. Within this framework, individual effect sizes as reported by each study are treated as stochastic, allowing for the dissection of the overall effect into distinct between-study and within-study effects.

To investigate potential publication bias, we employed funnel plots, with a specific focus on contour-enhanced funnel plots (Palmer et al., 2008; Peters et al., 2008; Sterne & Egger, 2001; Sterne & Harbord, 2004). This innovative enhancement involves the incorporation of statistical significance contour lines onto the funnel plot. By overlaying contour lines corresponding to predetermined significance levels (0.01, 0.05, and 0.1) for studies with null effect sizes, we could discern patterns that may indicate the presence of publication bias. Specifically, a dearth of research, particularly among smaller studies, within regions of no significance on the funnel plot might signify the existence of publication bias. Conversely, if such bias is not evident, the observed asymmetry within the funnel plot could be attributed to other factors other than publication bias.

Additionally, the Egger test, originally proposed by Egger et al. (1997) , was incorporated into our analysis. This test involves the assessment of the slope from a weighted regression of the effect size against its corresponding standard error, with potential adjustments for moderator variables. The test is given by the following regression.

$$y_i = \alpha + \beta * se_i + \varepsilon_i \text{ where, } \varepsilon_i \sim N(0, se_i^2 * \varphi) \qquad (7)$$

where y_i is the observed treatment effect of intervention i on its standard error (se_i) weighted by the inverse variance and φ is the multiplicative dispersion parameter in the data that allows for heterogeneity inflation. The aim is to discern any potential bias stemming from asymmetry within the funnel plot. Furthermore, we applied the trim-and-fill method to gauge the potential impact of publication bias on our final conclusions. This iterative technique involves estimating the number of potentially missing studies due to publication bias at each iteration stage. Subsequently, during the final pooling stage, the effect sizes and standard errors of these hypothesized missing studies are imputed and incorporated into the overall collection of studies, yielding an adjusted estimation of the overall effect size. This approach adds a layer of robustness to our inference by accounting for potential publication bias effects. During our meta-analysis, we thus far address the inherent heterogeneity present in estimating the overall effect size.

Finally, we implement meta-regressions to assess the remaining heterogeneity across studies to assess the true effect of interventions on outcomes of interest. While meta-regressions closely resemble conventional regression analysis when individual-level data are accessible, they remain distinct. In meta-regressions, the focal points of observation are the individual studies, with the effect size constituting the primary outcome of interest. Notably, the covariates involved are documented at the study meta data. These covariates, referred to as moderators, encapsulate pertinent study-level characteristics. The core purpose of meta-regression lies in the exploration and elucidation of the heterogeneity existing between studies, achieved by scrutinizing the interplay of these moderators. The moderators in our analysis were country of study, sample size, the methodology employed for impact assessment, the presence of replication, the proportion of treated units within the dataset, and the duration of observations. Through this meticulous consideration, we aimed to unravel the elements contributing to the observed heterogeneity in effect sizes across the spectrum of studies. The outcomes yielded by our meta-regression analysis shed light on the precise factors that underpin the variations in effect sizes among the included studies. This revelation allows for an interpretation akin to that of a standard regression analysis, wherein the moderators are evaluated for their influence on the effect size.

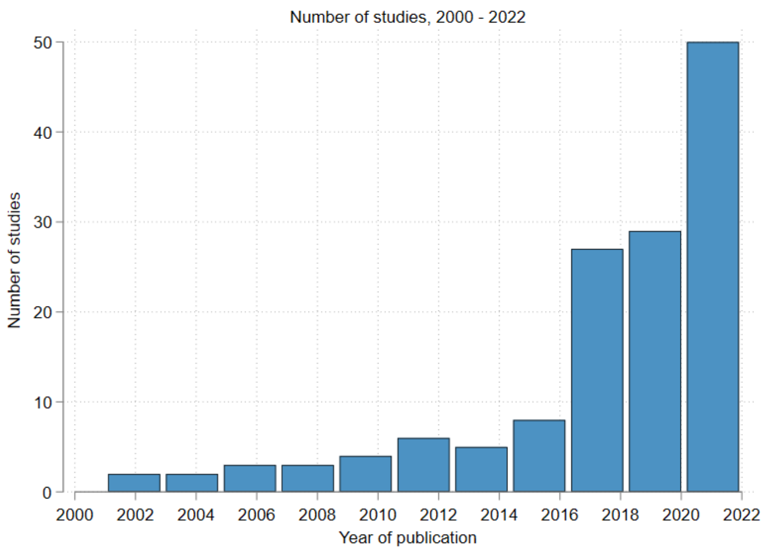
The assessment of the effects of agricultural technologies and sustainable natural resource management practices was categorised in four classifications, namely: (1) farm productivity, (2) household welfare measured in the form of income, (3) food security (including consumption) and (4) environmental sustainability. As per our pre-registration, we intended to measure effects on environmental sustainability. However, our literature search did not yield any studies assessing any dimensions of this outcome. The results presented here therefore do not have any environmental sustainability outcomes. All meta-analysis was conducted in Stata 17 using the *meta* set of commands.

3. Results

3.1.Description of the data

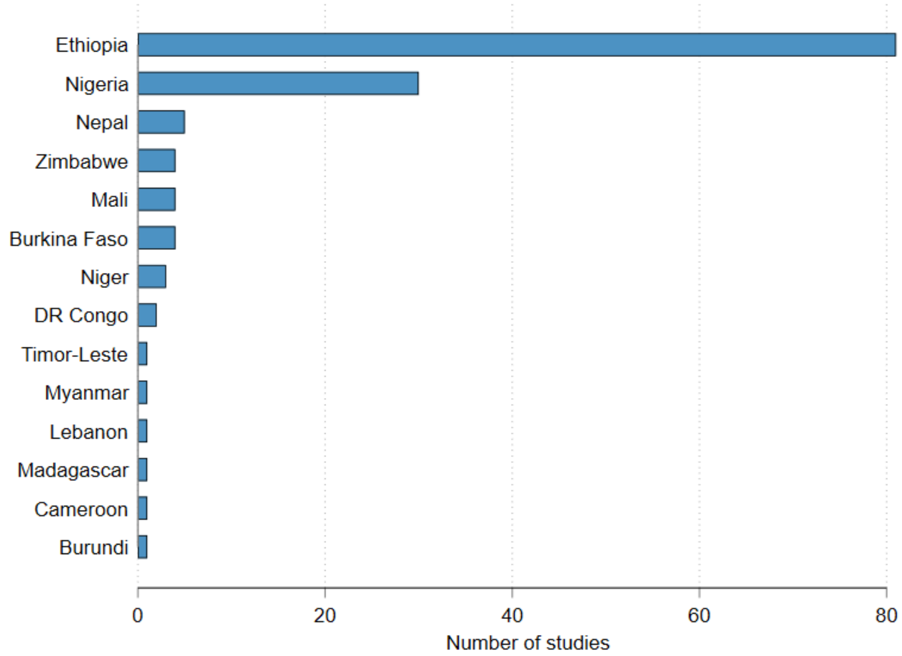
To assess the determinants of adoption of agricultural technologies and natural resource management practices, we reviewed 132 peer reviewed studies. The number of publications has grown in the last 22 years. The studies reviewed increased just about 2 studies in 2001 to about 50 studies in 2022. However, the largest jump was experienced in 2017 with the number of studies increased from just about 8 studies to about 27 studies.

Figure 2: Number of studies per year (2000 - 2022)



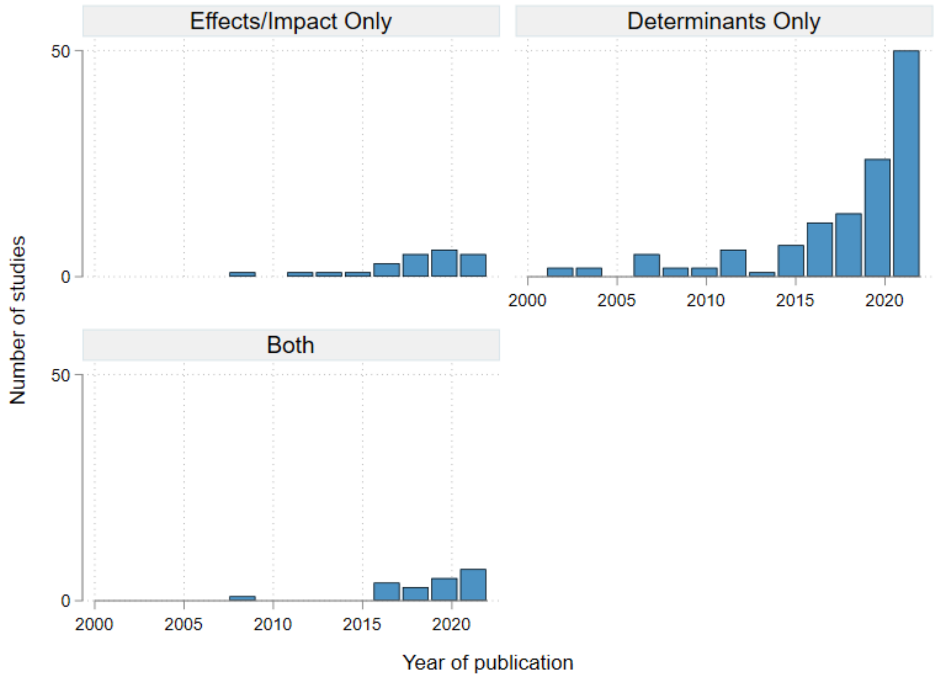
The geographical coverage of the studies was not diverse. Of all the studies included in the review, 81 of the studies came from one country, Ethiopia. An additional 30 were from Nigeria. All the other countries that had at least one study included had only single digits numbers. The majority of the studies were from Africa with only Nepal (5 studies) Lebanon, Timo Leste and Mynamar (1 study each) having any non African representation. In terms of the type of vulnerability, we did not include any country with climate vulnerability. All the studies were from countries which has a voilent conflict-related vulnerability.

Figure 3: Studies by country



Some of the studies covered both adoption and others covered only impact while others covered both. We categorised the studies into this thematic coverage. Many of the studies covered only the determinants of adoption of technologies. The number of studies related to determinants only increased from about 1 study in 2001 to about 50 studies in 2022. Studies covering both impacts and determinants of adoption emerge only after 2015. For the decade of 2000 to 2010, only one study (Kassie et al., 2009) covered impact of adoption of various technologies before 2010. The study compared plots with inputs (chemical fertiliser) or compost and compared with no inputs or compost. The study found that comparing compost (organic fertilizer) with no inputs, increased teff production (measured in tons per hectare) by 59%, wheat by 48% and barley by 35%. Plots using compost produced 19% more teff, 38% more wheat and 19% more barley compared to those that applied chemical fertiliser. They also found that plots with chemical fertilisers compared to no fertilisers has 40% more teff production, 27% more wheat and 24% more barley. The conclusion was that compost (organic fertiliser) was more effective in increasing productivity compared to those that used chemical fertiliser and those that did not apply anything. Chemical fertilisers were also significantly more effective than no fertiliser at all. Figure 4 shows number of the studies by theme across the years.

Figure 4: Number of studies by Study Thematic Area

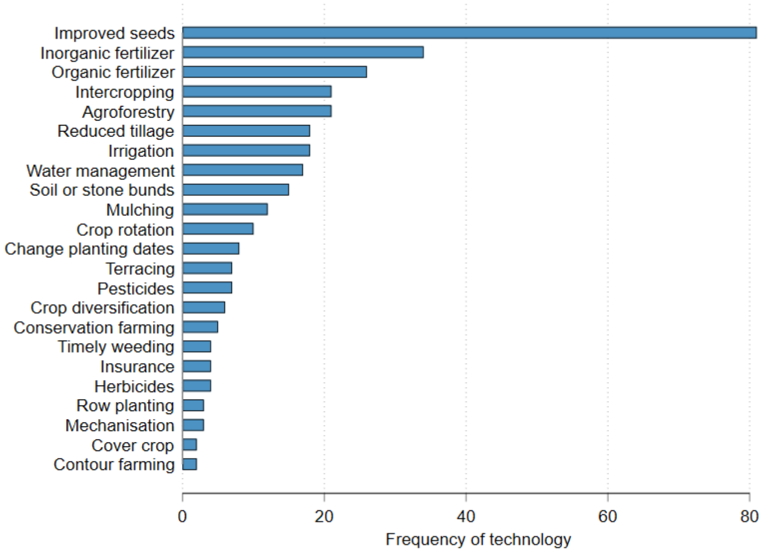


3.2. Adoption of agricultural technologies

3.2.1. How much are different technologies adopted?

From 132 studies, 328 technologies were registered. Since these technologies were not unique across the studies (for instance, some studies assessed organic fertilizers while others assessed manure. In both studies, organic fertilizer is the underlying technology), we aggregated them into 23 unique technologies. Figure 5 below records the frequency of each of the 23 unique technologies. The most common technology was use of improved seeds, which was recorded listed in 81 papers. Improved seeds included hybrid and drought resistant varieties. The second most common technology was use of chemical fertilisers recorded in 34 studies and organic fertilisers recorded in 26 studies was the third highly prevalent technology. The least common technologies were contour farming recorded in only two studies (Diarra et al., 2021; Ouédraogo et al., 2017) and use of cover crop, also recorded in two studies (Bayu, 2020; Diarra et al., 2021). Mechanisation and row planting were also recoded in three studies each and agricultural insurance was recorded in five studies (Aizaki et al., 2021; Belissa et al., 2019, 2020; Budhathoki et al., 2019; Ndagijimana et al., 2020).

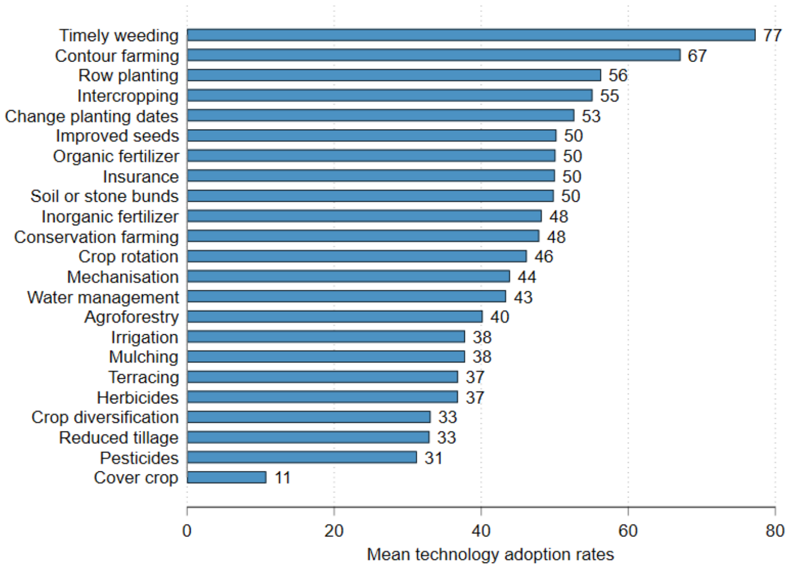
Figure 5: Frequency of technologies



3.2.2. Mean adoption rates

We averaged their adoption rates in each study to compute a mean adoption rate for each of the 23 technologies. Results in Figure 6 below show that most adopted technology was timely weeding whose average adoption rate was 77%. The most frequent technology, improved seeds had an adoption rate of only 50%. Organic fertilizer also had an 50% average adoption rate. The least adopted technology was use of cover crop, which had an average adoption rate of only 11%.

Figure 6: Mean technology adoption rates

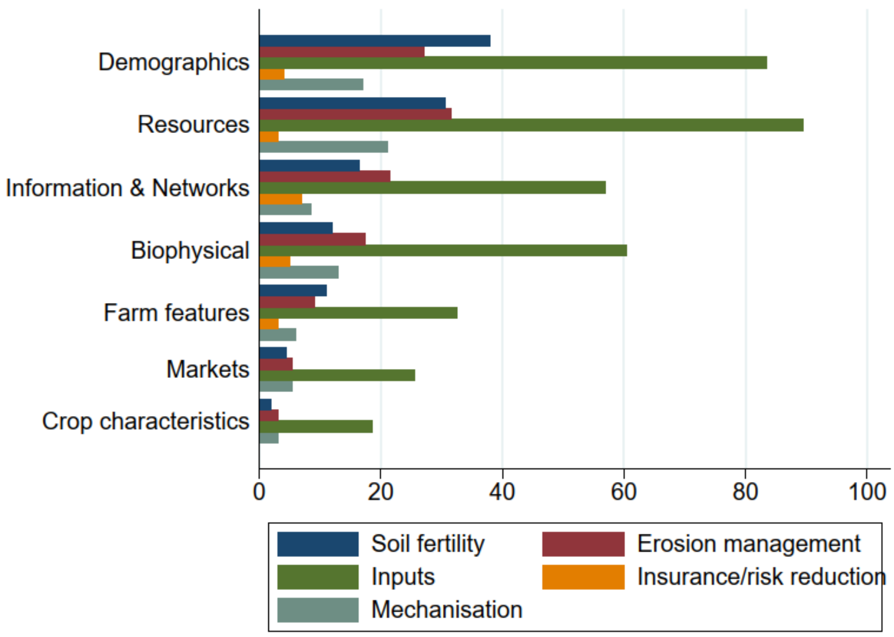


3.2.3. Determinants of adoption

The determinants were recorded in their text format and were summarised in two dimensions.

First, we recoded 1448 coefficients from 132 unique studies. We then investigated all the texts describing the coefficients (coefficient descriptions) and classified them into seven categories corresponding to household demographic determinants, resource determinants, information and networks, biophysical determinants, farm features, markets and finally crop characteristics. Our categorisation was tangentially inspired by the categorisations in Teklewold et al. (2017). Figure 7 shows the number of coefficients extracted per determinant category and technology type. The largest number of coefficients/ effect sizes was recorded on input technologies. Input technologies basically include fertilisers and improved seeds. We observed that about 51.4% of all the coefficients collected were for input technologies. In all the seven categories of coefficients collected, input technologies dominated. About 15.8% and 15.7% of the coefficients collected were in soil fertility and erosion management technologies.

Figure 7: Frequency of the determinants of adoption by technology type



The rest of the coefficients concerned mechanisation technologies (10%) and just over 2.6% of the coefficients were for insurance and other risk reduction technologies. A slightly higher number of coefficients on insurance and risk reduction were categorised in information and networks while no coefficient on this technology type was recorded on either markets or crop characteristics.

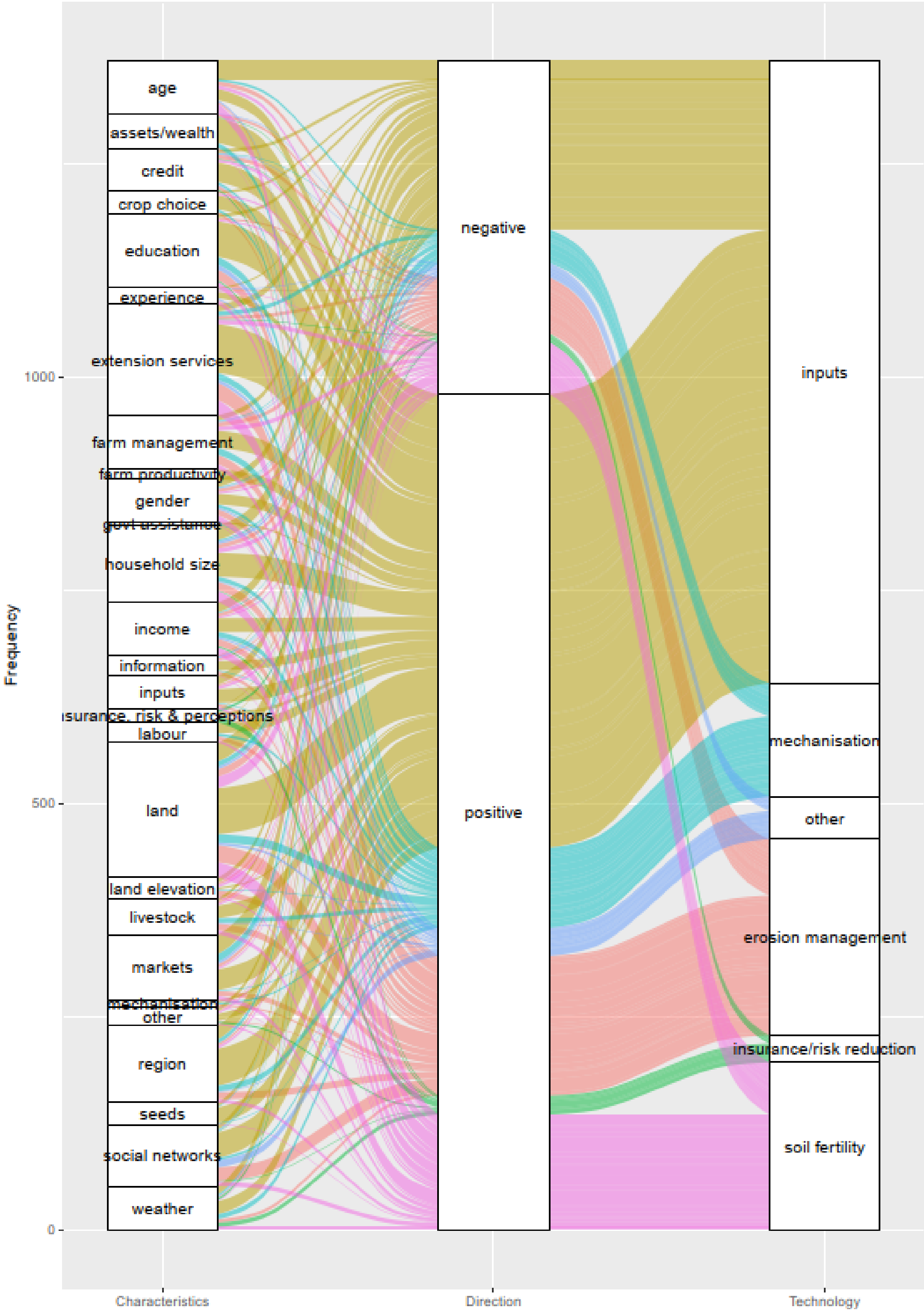
3.2.4. Direction of relationship between characteristics and technology types

After categorising determinants, we were interested in exploring the relationships between characteristics, their direction, and the technology types they predict. We visualized the relationship between different characteristics and technology categories (inputs, erosion management, insurance risk reduction, soil fertility, mechanisation) using a Sankey diagrams.

In Figure 8, we show the relationship between all the 30 characteristics and the technology types, mediated by the direction of the relationship. Almost all the determinants of adoption have a negative and positive association highlighting on their presence or absence. The most prevalent determinants were extension services and land size, regional variation, education, markets, and household size. Government assistance through subsidies, farm productivity, risk, and perceptions (mainly about insurance) and mechanisation were the least prevalent determinants. This observation somehow contrasts what we observe in the previous analysis of determinants with the highest contribution to adoption. For instance, in the previous analysis, we observed that mechanisation was prominent in contribution to adoption of almost all technology types. For instance, of all the 115 unique studies included in the review (counting multi-country studies as one), mechanisation as a grouped predictor variable was observed only in six studies (Dhakal et al., 2015; Gebremeskel et al., 2018; Sertse et al., 2021; Tadesse & Belay, 2004; Teshome et al., 2021; Verkaart et al., 2017). That the contribution of mechanisation comes from only a handful of observations might imply that its overall contribution is likely much lower.

Looking at the direction of association, we observed that most determinants extracted were positively associated with adoption than negatively associated. Looking at the right-hand side of Figure 8, we can observe that the technology types that had the largest representation in the review are inputs. Almost half the coefficients extracted were associated with adoption of inputs. These are mainly seeds and fertilizers. A smaller number of coefficients assess erosion management technologies and soil fertility technologies (excluding fertilizers and pesticides). A very small number of papers present technologies in their composite definition (e.g., improved agronomic practices) and we are not able to recategorize these into any of the five pre-defined categories. For these, we created an additional category called “other” so that they are not dropped from analysis. Looking at the largest technology category, we observe that a large component of its predictors is positive. The leading predictors of inputs adoption were land, extension services, education of the farmer and to some extent, household size which might also be a proxy for availability of household labour. However, we note that the predictor variable age was more negatively than positively associated with inputs adoption. Older farmers are therefore less likely to invest in farm improving inputs as compared to younger farmers. Almost all the other technology types tend to be more evenly distributed in their predictors with no clear dominating predictor. In addition, predictors of all other technology types are more positive. Overall, negative predictors provide only a small component of predictors of each technology type.

Figure 8: Sankey diagram of relationships and weight/strength of relationships between determinants and technology types

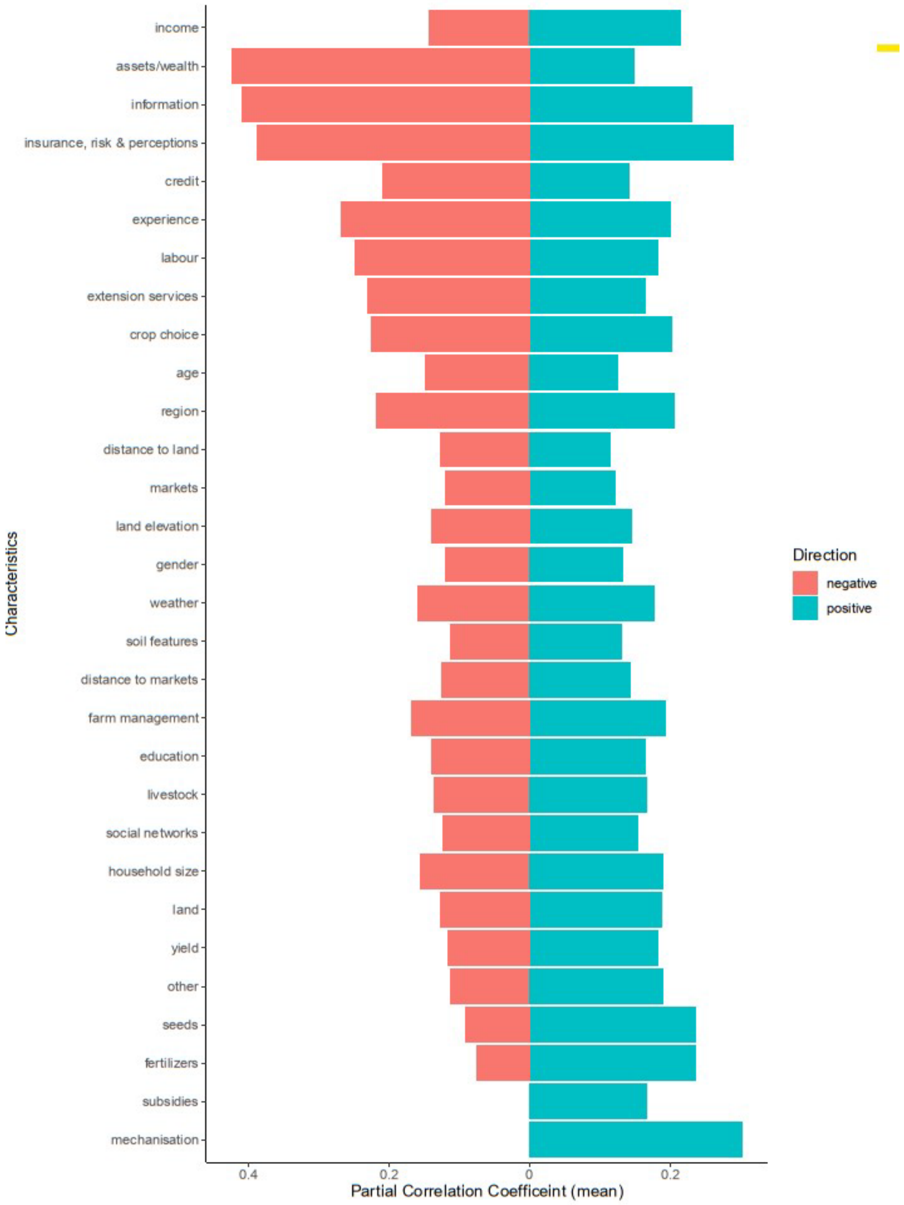


3.2.5. Descriptive Results of Partial Correlation Coefficients of Adoption

3.2.5.1. General Determinants of Adoption

We then conducted a more detailed categorisation of the determinant variables into 30 categories. For each determinant, we recoded its coefficient, both positive and negative. In Figure 9, we used a divergent bar plot to visualize the partial correlation coefficients for association all identified characteristics with overall adoption. All the coefficients are standardised by their standard errors and weighted by the sample size of the study. The composite result of all technologies and all outcomes is shown in Figure 9 below.

Figure 9: Average association of composite determinants of adoption



From Figure 8, we observed that almost all variables had a negative and positive relationship with adoption. This finding was also observed by Arslan et al. (2022), though for them to a smaller extent. The differences with their study might emanate from how this study coded the variables. For instance, we coded both land size, land tenure as “land” while in their study, these were differently coded, with land size having a more positive relationship and land tenure and fragmentation having a more negative relationship with adoption. The results therefore throughout these studies need to be taken in consideration to how different researchers have made unique researcher decisions regarding coding. Overall, the variables with the largest contribution to adoption were mechanisation, availability of seeds and fertiliser, insurance and perceptions and income. However, assets/ household wealth, availability of information and risk perceptions were also observed to have more negative association with adoption decisions. For each of these characteristics, their association with adoption was also large, implying that availability of these functions and assets were enhancers of adoption and their unavailability or availability in limited quantities were associated with low adoption.

Mechanisation and fertilizers are most likely to reflect path-dependence based adoption behaviour. The categorisation of mechanisation included variables such as access to technology, access to irrigation technology, and animal traction. Essentially, the variable measures knowledge, access, and use of various mechanisation technologies. The implication here is that farmers who have previously used mechanisation technologies and fertilizers are more likely to continue using these technologies hence increasing the average adoption levels.

Generally, access to information about technologies largely aids the adoption decision. Various studies (Gebre et al., 2019; Teklewold et al., 2017; Zakari et al., 2022; Zeleke et al., 2022) establish this fact that access to information about markets, climate, seeds availability among others increased the probability of innovation uptake. The most common innovations associated with access to information were inputs, erosion management and soil fertility. The strong negative correlation shows that absence of information was also associated with lower adoption. Moreover, to some extent information circulates not only through mass media platforms such as radios but also through extension workers. We therefore observe that the presence or absence of extension services was also associated with technology adoption.

Many innovations are better applicable to flat lands. For instance, mechanisation and erosion management technologies are more suited for less steep land. Land elevation was therefore strongly predictive of technology adoption. Households that own plots of land on more elevated places are less likely to adopt technologies (Bedeke et al., 2019; Kassie et al., 2009; Teklewold et al., 2017). The technology categories most affected by elevation were soil fertility, input use and erosion management.

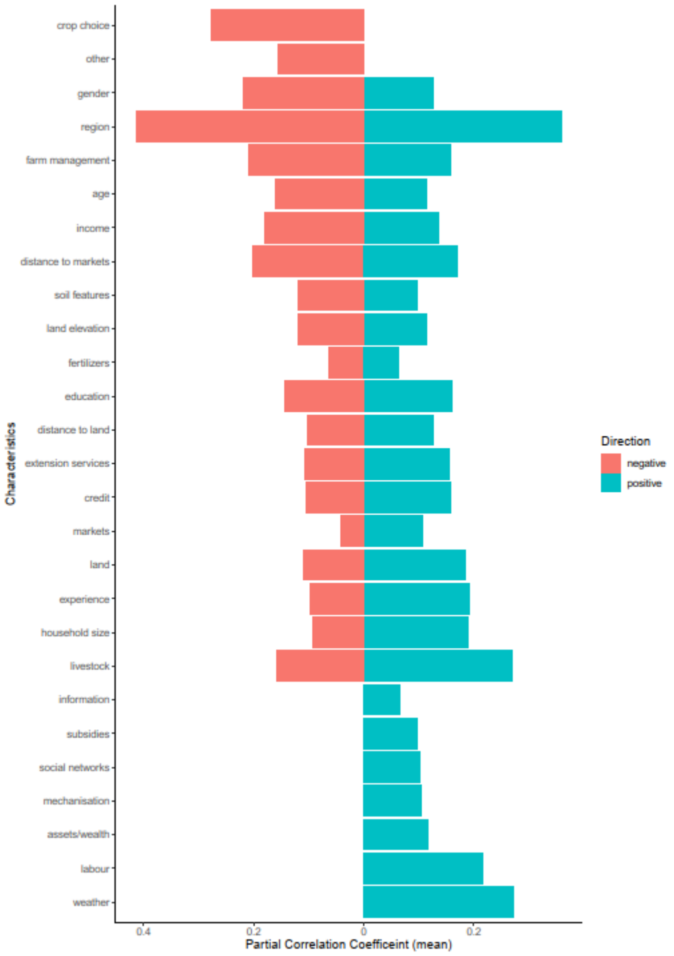
Another variable to highlight is region. The variable region captures regional differences in adoption rates. This variable was more important for studies that were nationally representative, or those that capture some differences across regions by including regional dummies in their regressions, for which regional differences were able to be explored. For instance, Teklewold et al. (2017) highlights on regional variation in erosion management and input technologies in Ethiopia, Gebru et al. (2021) and Gebru et al. (2020) and highlight on regional variation in input use in Ethiopia. Regional variation in mechanisation is also reported in Burkina Faso (Yaméogo et al., 2018), Nigeria (Obayelu et al., 2016) and Ethiopia (Diro et al., 2022; Gebru et al., 2020); input technologies in Nigeria (Abdoulaye et al., 2018; Awotide et al., 2016; Obayelu et al., 2016), Ethiopia (Abera et al., 2020; Asfaw et al., 2019; Habtewold, 2021) among others. Within countries, some regions are more likely to have higher adoption rates than others, potentially due to residual and historical experiences of other factors (such as education, wealth, and others) that might be influenced and drive regional differences.

3.2.5.2. Determinants by technology type.

Soil fertility management technologies

We further estimated the weighted mean association of various determinants on the different technology categories. First, we start with soil fertility management technologies which included non-chemical applications to land to keep it or increase its fertility. Figure 10 provides this summary.

Figure 10: Magnitude of coefficients across soil management technologies

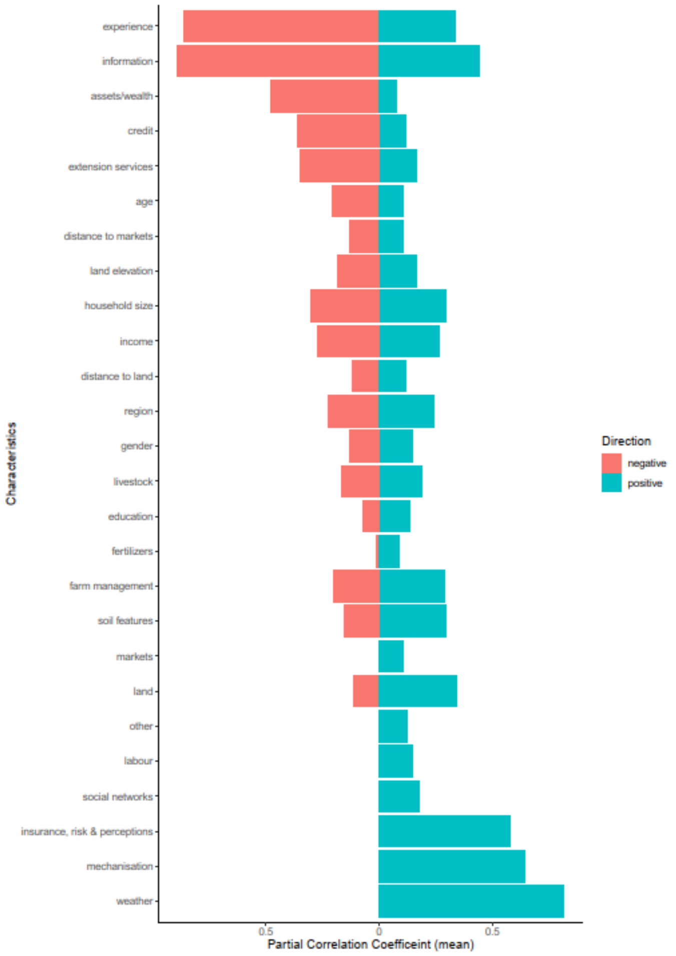


Weather, availability of labour, household assets, access to mechanisation technologies (specifically irrigation systems), social networks, subsidies and access to information were found to have only a positive association with adoption or fertility management technologies. However, household ownership of livestock and regional variations were they drivers of erosion management technologies. On the other hand, crop choice, gender, farm management practices, distance to markets and livestock, again, had the largest negative associations with soil management technologies.

Erosion management technologies

Figure 11 shows the determinants of erosion management technologies. The determinants with the largest contributions to these types of technologies were weather, access to mechanisation (mainly irrigation), access to insurance and other risk management technologies, and to some extent, access to information and farmer experience. However, experience and access to information were also the characteristics with the largest negative associations. Assets, access to credit and extension services also tend to have a more negative than positive association with take up of erosion management technologies.

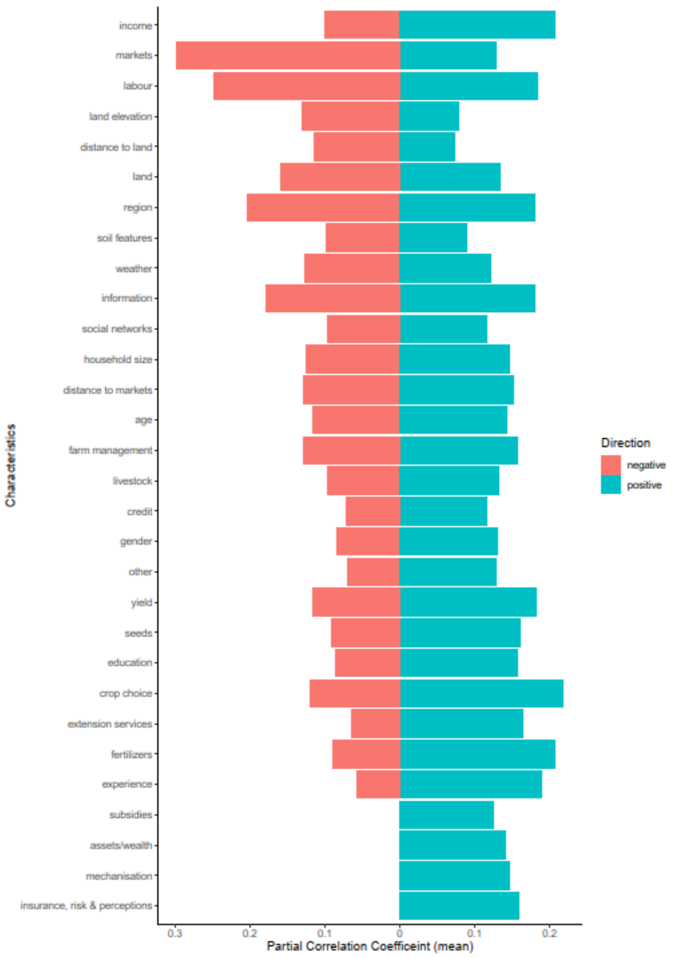
Figure 11: Magnitude of coefficients across erosion management technologies



Chemical input technologies

Figure 12 depicts the coefficients across input technologies. The determinants for input technologies (chemical fertilisers and pesticides) are a lot more varied than in other technologies. Subsidies, mechanisation potential and assets/wealth and risk perceptions were observed to have only positive associations. On average, each of the 30 characteristics highlighted in the studies had a 0.1 – 0.2 (10-20%) association with household adoption of input technologies. This was different from other studies where the variation across characteristics of determinants was far wide. Highlighting on some of the key contributors, income, labour, crop choice and information were some of the more prominent determinants. Previous fertilizer use, potential yield expectation and farmer experience are also of note. We also observe significant regional variation, implying that within countries, some regions were more adopters than others. Looking at the negative associations, markets, labour, and access to information were key. Regional variations are also abounding, underlining existing regional differences. Availability of markets is an important finding. A lot of policy and public conversations do not usually highlight the last mile delivery of inputs such as fertilizers. This finding therefore clearly shows that availability of markets and distribution channels as well as conducive prices are key for adoption. In their absence, uptake is low.

Figure 12: Magnitude of coefficient across characteristics for inputs

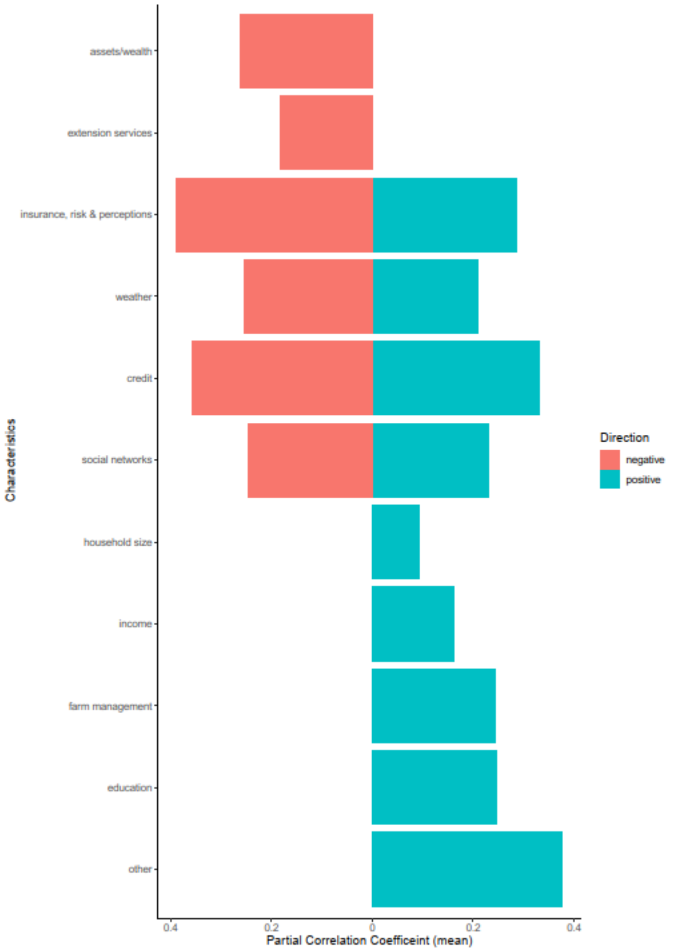


Insurance and risk management technologies

Regarding insurance and risk management technologies, the first key observation was that compared to other technologies, risk management technologies have fewer determinants. The number of point estimates entering the insurance and risk management model was very low, showing how this remains a largely understudied theme in conflict affected and fragile countries. Of the 139 papers included, only 5 papers covered insurance technologies comprising of only 2.6% of the coefficient estimates extracted. Figure 13 below shows the PCC results, revealing that of the 30 determinant characteristics only 11 showed up in the PCC model. The estimated included were Aizaki et al. (2021) on weather index insurance in Myanmar, Budhathoki et al. (2019) on index based insurance in Nepal, Belissa et al. (2019) and Castellani

& Viganò (2017) on weather index insurance in Ethiopia and Ndagijimana et al. (2020) on index insurance in Burundi. Moreover, these studies were also from only 6 countries (Burundi, Ethiopia, Myanmar, and Nepal), further underling the thinness in number and distribution of studies assessing these types of technologies. Education, farm management, income and household size were all positive only determinants. Access to credit and perceptions about insurance and risk were also positive determinants but also had the largest magnitude of negative associations. As can be expected, most of risk management determinants can be linked to household economic conditions. Extension services and assets/ wealth have a negative association with uptake of the innovation. This is possibly driven by the number of estimates, in this case, being one. Budhathoki et al. (2019) observed that access to extension services reduced willingness to pay for agricultural insurance by 42% in Nepal and Castellani & Viganò (2017) also observe negative associations between household net worth between rich and poor households on willingness to pay for agricultural insurance in Ethiopia. It would be more than the case that more studies will find varying results that can change the direction of these effects. Nonetheless, it seems that households, in the case of Budhathoki et al. (2019) might tend to perceive that better extension services can improve their yield, provide them with potential knowledge for protecting against shocks and hence reduce the potential demand for insurance.

Figure 13. Magnitude of coefficient across characteristics in insurance and risk management technologies

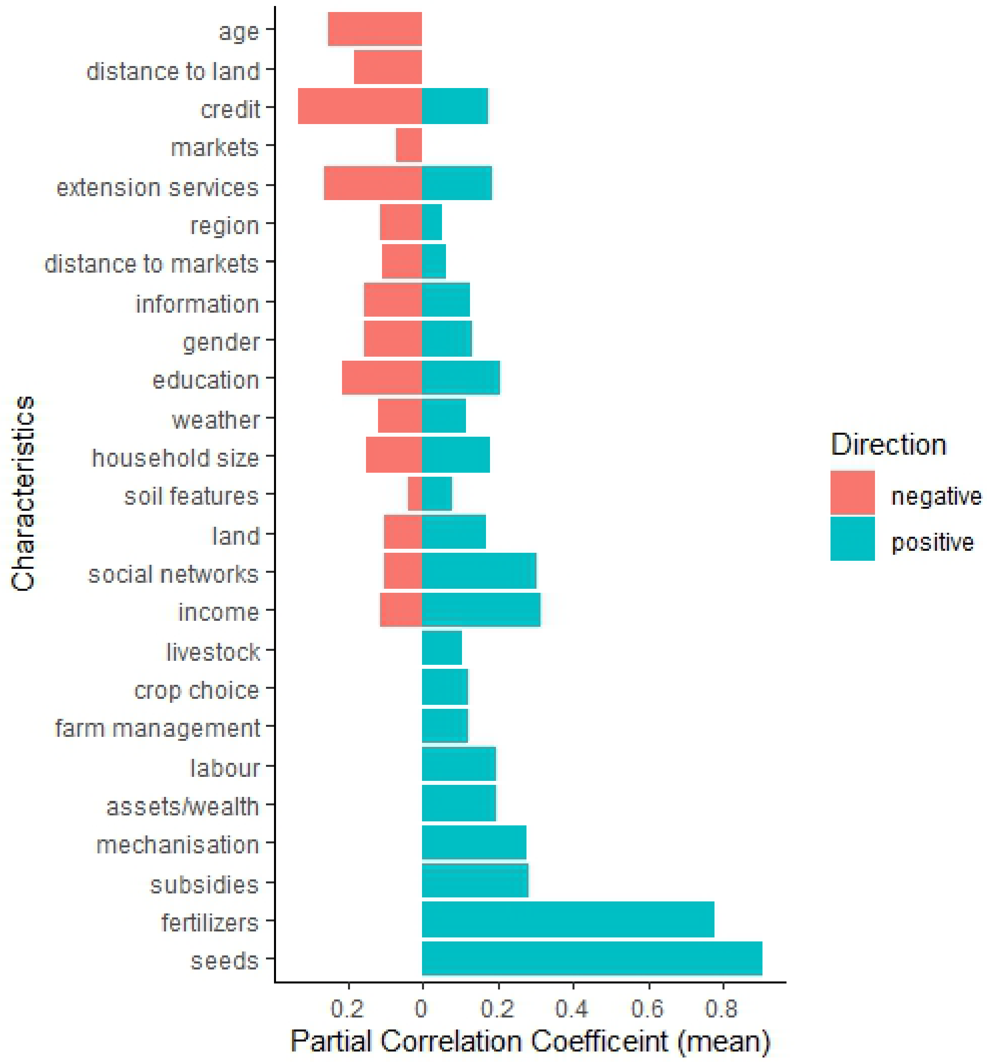


With the above, the findings on risk perceptions and credit are therefore less surprising. While Aizaki et al. (2021) and Belissa et al. (2020) found the risk perceptions were more likely to lead to increase in demand for insurance, Castellani & Viganò (2017) find the opposite. In our analysis as the strength of the direction of association is less clear, more studies are needed for policy and intervention targeting to be efficient.

Mechanisation technologies

Our findings on mechanisation technologies in Figure 14 show a couple of important points. First, a lot more characteristics have only positive associations than in other technologies. Of the 25 characteristics that were found to determine adoption of mechanisation technologies, nine (9) were only positive. This provides a potentially promising entry point for policy innovation as factors are predict uptake are already more clearly identified (Arslan et al., 2022). Secondly, for the two characteristics that have higher magnitudes of determinants, the mean association was much higher in mechanisation than in any other technology category. For example, improved seeds and fertilizers were associated with increasing uptake of mechanisation by magnitudes of over 0.8 (80%) while in all the other technology types, the magnitude was lower than 0.2 (20%). Income, social networks, access to extension services, education and access to credit services were also strong predictors of adoption of mechanisation technologies. On the opposite, education, access to credit, age and access to extension services were associated with adoption in negative magnitudes. Older farmers, less education farmers, those who lack credit are less likely to take up mechanisation.

Figure 14:Magnitude of coefficient across characteristics for mechanisation

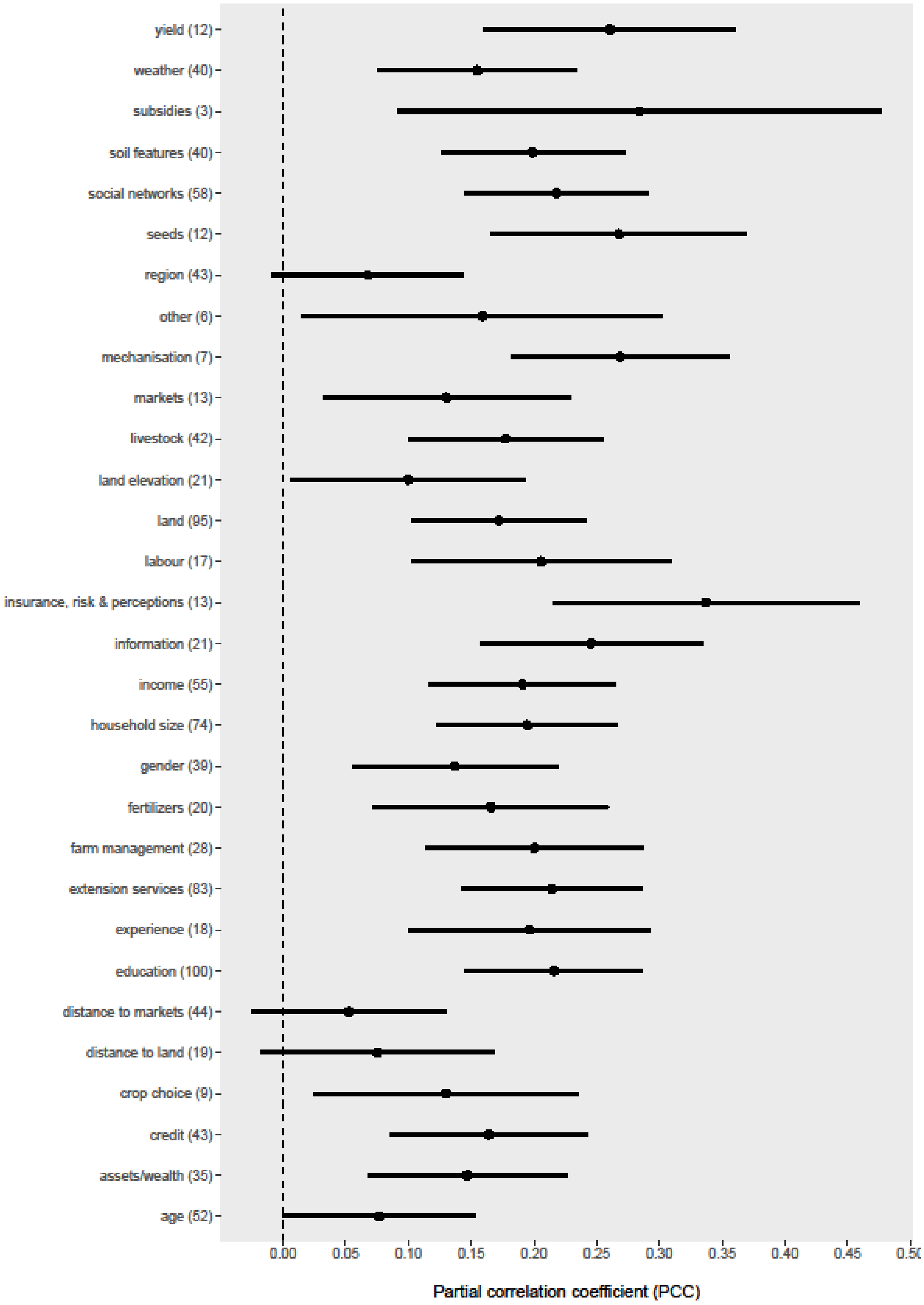


3.2.6. Multivariate partial correlation coefficients meta-regression for determinants of technology adoption

Results of a multivariate PCC model to explain how each characteristic was associated with adoption of technologies are shown in Figure 15 (and the tabular results in supplementary Table S2). The point estimates are plotted with the confidence bars. The confidence bars partly reflect the precision or lack of it given the number of observations being assessed. This therefore implies that wider confidence intervals are more likely to abound when there are fewer observations and the higher the number of observations, the more precise the estimated coefficient of the characteristic. The results show that most of the characteristics other than distance to land, markets, land elevation and the region has a significant and positive relationship with adopting agricultural technologies in conflict and fragile countries.

First, we start with the characteristics that had the highest adoption correlation coefficients. The results show that subsides and insurance were the most highly correlated with the technology adoption. Fairly priced insurance premiums were associated with higher insurance acceptability and willingness to pay (Aizaki et al., 2021) and having positive perceptions about insurance products (Chalak et al., 2017) including perceiving technologies such as improved maize as less risky (Lawal et al., 2004) was likely to increase uptake. Offering subsidies increases uptake of fertilizers (Teklewold et al., 2017), drought tolerant seeds varieties (Ouédraogo et al., 2019) and intercropping technologies (Ngaiwi et al., 2023).

Figure 15: Partial Correlation Coefficient graphed results



Other key determinants were access to information, previous utilisation of technologies such as seeds and fertilisers. For seeds, the coefficient was significantly larger in size and significance levels. Previous use of fertilizers also is strongly significantly associated with adoption. These results imply that adoption has strong experience, learning and lock-in tendencies such that farmers who used a given technology before are likely to continue using it.

Possibly, what is less surprising are the variables that were not significant, that is distance to land, distance to markets and to some extent regional variation. For the distance variables, it is compelling that variables that measure access and presence of innovation within the reach of a farmer were significant (e.g., markets, income, credit, assets). This implies that generally geographical access is potentially attenuated with economic access such that when technologies are present and affordable, farmers are more likely to adopt them even in the face of spatial barriers.

We further estimated the relationship between the characteristics and technology by categories. The results are show in the supplementary materials Figures S1 to S5. The results for soil fertility management shown in Figure S1 show more variation and the imprecision in estimates. Of the 27 characteristics that entered the model, only weather, livestock ownership, land, household income, household size, extension services, education, farmer experience and household wealth were significantly associated with adoption. Figure S2 shows results of erosion management and reveals that soil features, social networks, access to mechanisation availability of labour, insurance and risk perceptions, household size and farm management practices. Risk perceptions had the largest magnitude of association with erosion management technologies. Though this was driven by one observation from Chalak et al. (2017) who observed that having positive perceptions about conservation agriculture was associated with increasing the odds of willingness to adopt conservation agriculture by more than four times.

Results for adoption of inputs are shown in Figure S3. The results reveal that first, more data entered the PCC model more than the other assessment. Secondly, all the 30 characteristics entered the model implying that far more characteristics explained input adoption than other technologies. In 77% of the characteristics, the association was positive and significant. Age of the farmer, distance to land, distance to land, gender, land elevation and subsidies were insignificant in addition to the characteristic "other" which compiles a small number of estimates that were too diverse to fit into one of the other 29 categories.

Figure S4 shows the results for risk management technologies – specifically insurance. Only eleven characteristics entered the model. None of the characteristics sufficiently shown strong predictability of adoption. Risk management technologies such as agriculture insurance have faced extensive barriers and take up has remained very low across many low income countries (Nshakira-Rukundo et al., 2021). It is therefore not a surprise that we fail to observe any compelling characteristics among conflict and fragile countries, most of them in Africa. Finally, Figure S5 shows results for mechanisation technologies. Twenty-five characteristics entered the PCC model and show that a rough mix of significant and insignificant characteristics that predicted mechanisation technologies' adoption. Of the 30 characteristics that entered the model, 10 were positively associated with adoption. Previously use of improved seeds is likely to increase adoption of mechanisation technologies. Though this was a singly observation (Gebru et al., 2020). We can also highlight on farmer age which had a negative coefficient though marginally outside the bounds of conventional significance. The message though might be that older farmers are less likely to adopt mechanisation technologies.

In general, our analysis offers two insights. The first one is that for policy makers interested in increasing adoption rates of agricultural and natural resource management technologies in conflict and fragile countries, with some level of caution, this analysis can guide them on targeting the characteristics that can increase adoption. The second is that risk management technologies such as insurance or risk contingent credit and others related issues remain poorly explained because of a dearth of relevant literature in this group of countries. More research is critically needed especially as policy makers increase their interest in agricultural insurance as a pathway of reducing climate and conflict related vulnerability.

3.3. Impact of Technology Adoption

The overall effect size from all technologies was 0.073, (95% CI 0.053 – 0.092), implying that on average an agricultural intervention could increase a given household outcome by 0.07 standard deviations.

3.3.1. Meta-analysis of the impact of crop and non-crop technologies

We then categorise the technologies into crop technologies, which are improved seed varieties and non-crop technologies which include all other technologies. Figure 16 below shows the forest plot for non-crop technologies. The overall effect size for non-crop technologies was 0.07 (95% CI 0.03 – 0.10). Studies that made the largest contribution to the effect size were Adhikari et al. (2018) who studied the effect of rain water harvesting for irrigation in Nepal, observing that households that adopted the technology had also had higher household incomes. Gebru et al. (2020) also studied the effect of road water harvesting (redirecting rural roads water runoff into plots) in Ethiopia and using propensity score matching observed that adopters increased crop yield, fertiliser use and household income. Zeweld et al. (2020) also studied the effect of contour terracing and animal manure application on cereal crop yield, per capita harvests, household income and asset holding and found significant positive results in all outcomes.

In Figure 17 shows the forest plot of the impact of crop technologies. The overall effect in this group of technologies was 0.08 (95% CI 0.06 – 0.10) indicating the improved crop varieties had a slightly higher effect on household outcomes than non-crop technologies. The key studies here were Etana et al. (2020) and Kassie et al. (2018) who study the adoption of improved maize technologies in Ethiopia and Oyinbo et al. (2019) who studied adoption of short season maize varieties in Nigeria. All these studies find large estimates of adoption.

Figure 16: Forest plot for impact of non-crop technologies

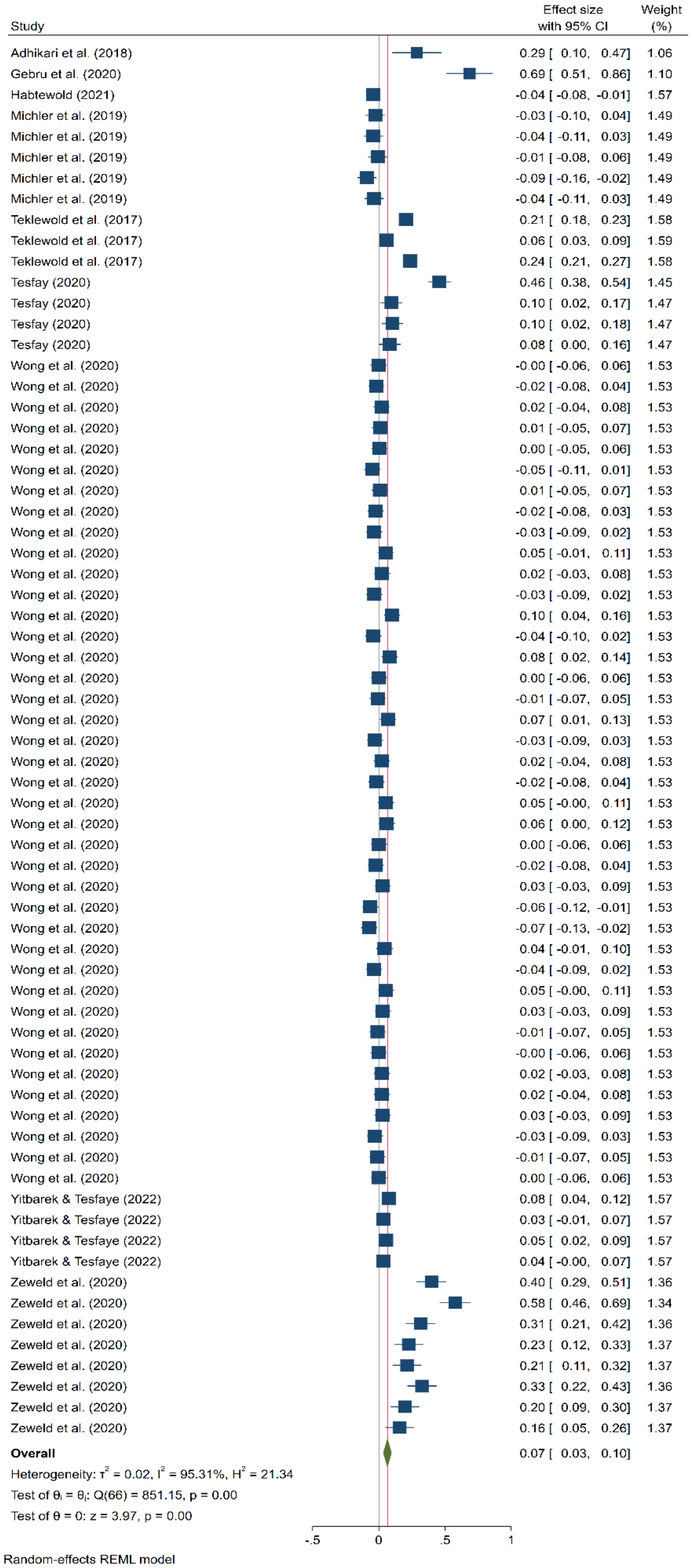
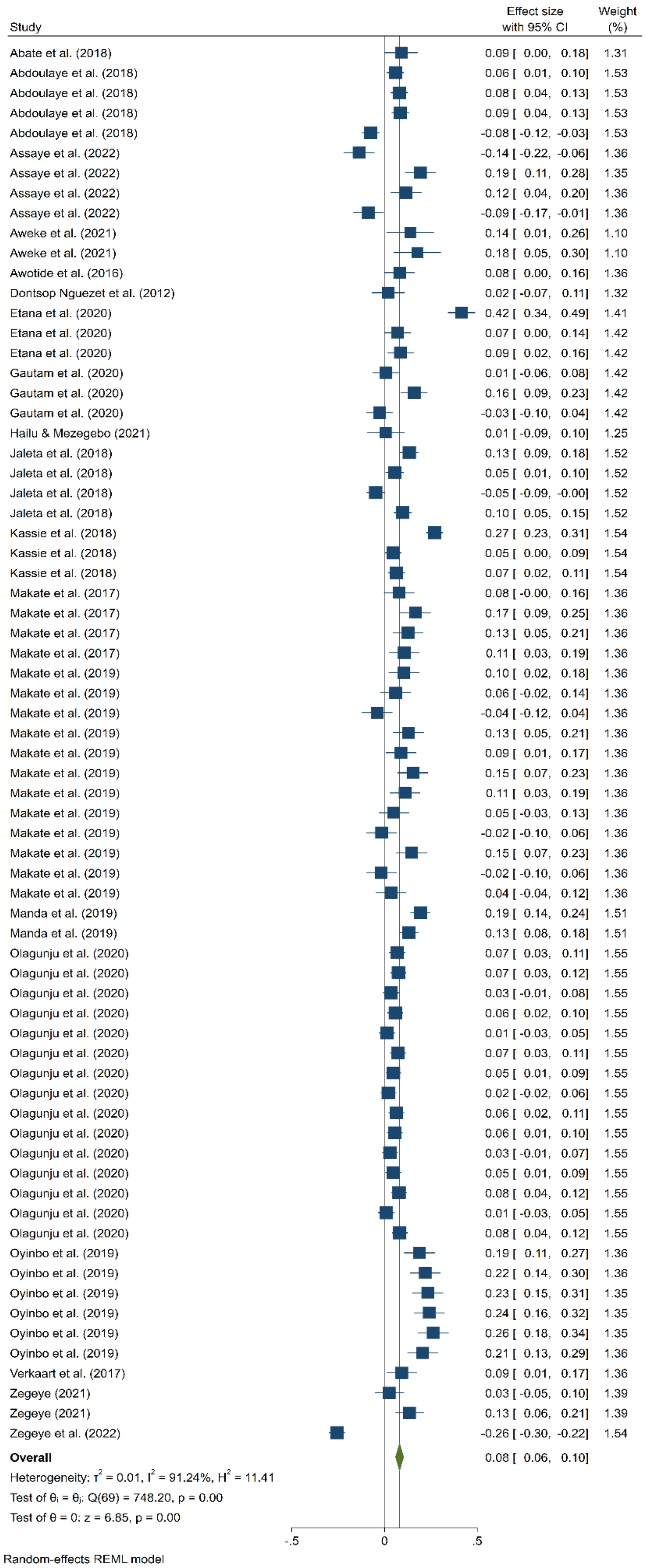


Figure 17: Forest plot for the impact of crop technologies



Furthermore, we categorise the data by outcomes across three groups of outcomes namely, household welfare (income), household food security and farm productivity. The effect size for technologies assessing farm productivity was 0.059 (95% CI 0.032 – 0.085) (Supplementary Figure S6). The effect size for technologies assessing household welfare was 0.085 (95% CI 0.055 – 0.115) (Supplementary Figure S8) and for household food security, it was 0.083 (95% CI 0.020 – 0.147) (Supplementary Figure S7). Overall, the largest effect size was observed in household welfare (including indicators such as income and poverty) and the smallest effect size was in farm productivity.

3.3.2. Heterogeneity between studies

Table 1 presents the results of the meta regression for examining the factors that are correlated with heterogeneity. The results highlight that country of the study, type of technology, the method used to estimate impact, sample size and replication in the study had a statistically significant effect on the overall effect size.

Table 1: Assessment of the drivers of heterogeneity in the study sample

Dependent variable- Effect size	Coefficient	Std. err.	P-value	Lower CI	Upper CI
Country					
Nigeria	0.29***	0.05	0.00	0.18	0.39
Zimbabwe	-0.18***	0.05	0.00	-0.27	-0.08
Nepal	-0.01	0.06	0.92	-0.12	0.11
Technology					
Non-crop technology	0.16***	0.03	0.00	0.09	0.22
Design					
Instrumental variables	0.06	0.07	0.44	-0.09	0.20
Matching/weighting	0.13**	0.05	0.02	0.02	0.23
Panel fixed effects	0.56***	0.09	0.00	0.38	0.75
Other	0.15	0.10	0.13	-0.04	0.35
Sample size	0.00***	0.00	0.00	0.00	0.00
Replication	-0.18***	0.06	0.00	-0.29	-0.06
Proportion of treatment	0.00	0.00	0.98	0.00	0.00
Treatment combination					
Combinations of treatments	0.14***	0.05	0.00	0.05	0.23
Length	-0.01***	0.00	0.00	-0.02	-0.01
Subgroup analysis					
Yes	0.13**	0.05	0.02	0.02	0.24
Constant	0.13**	0.07	0.06	0.00	0.27

Source: Own elaboration from model results (2023)

N= 1062. Significance levels correspond with ***1%, **5% and *10%.

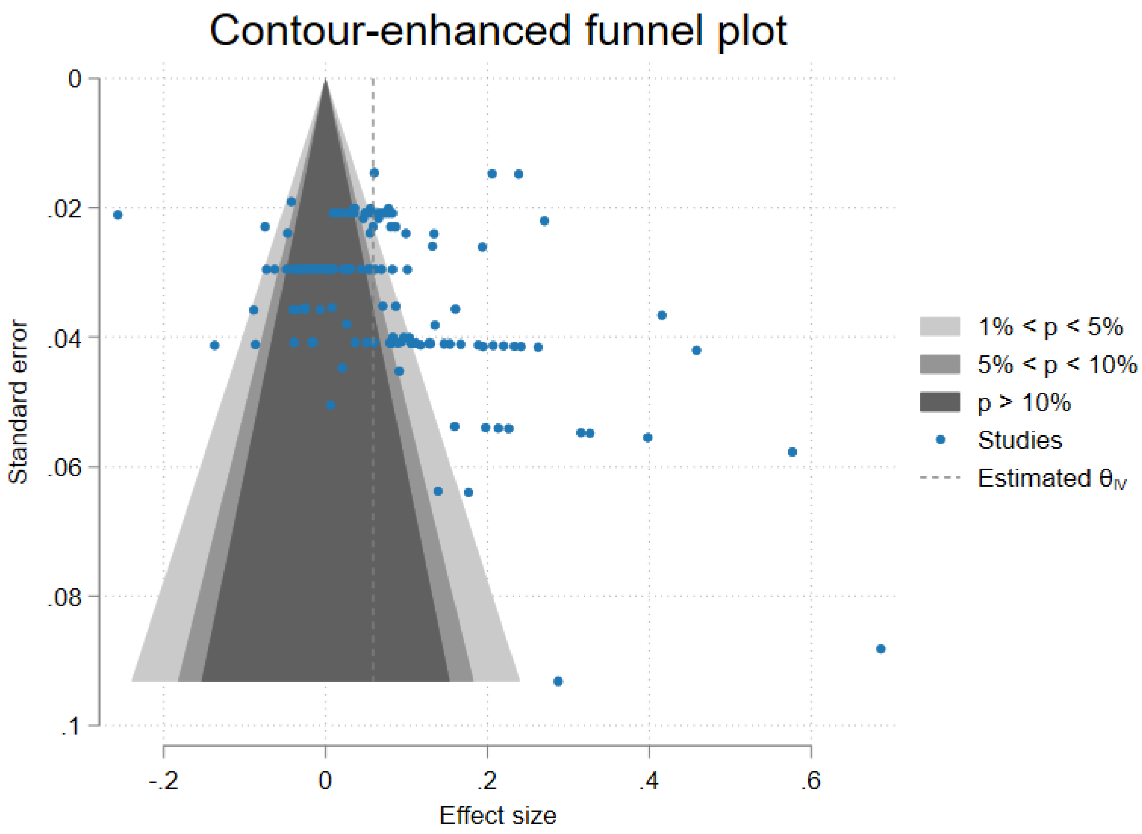
Publication bias is a major concern in the meta regression analysis. To examine the publication bias, we initially used a contoured funnel plot as given in Figure 3. If there were to be no publication bias, the studies are expected to be symmetrically placed within the funnel indicating 1, 5 and 10 percent level of significance. If there are studies to the right of the plot, it indicates small studies reporting large effects, and small studies with statistically non-significant results are not published, which is indeed the case. To formally test the small study effect, we have used the Egger's test, with a null hypothesis that there is no small study effect. Statistically significant test results indicate that there is small study publication bias.

One way of accounting for the publication bias is to perform the non-parametric trim and fill method, where some of the non- reported studies are imputed and the overall effect size is re-estimated. The results are given in Table 5. After adding the imputed values to account for the selection bias, the overall effect size is 0.057, which indicates a small but statistically significant effect.

3.3.3. Bias assessment and sensitivity testing in the studies

The Figure 18 provides a contour-enhanced funnel plot for all the studies included in the impact's meta regressions. From the funnel plot, we can observe that most of the studies are neither smaller size or larger size studies as we do not observe a cluster of standard errors around the zero or many smaller studies with larger standard errors further away from zero. Instead, we observe that most of the studies are or medium size, with standard errors clusters around the .02 and .06 area. We observe few instances were smaller studies (with larger standard errors) report larger effect sizes. These are just a few studies with standard errors beyond the .06 level.

Figure 18: Funnel plot for bias observation



Under the null hypothesis of no publication bias, we would expect a random distribution of standard errors such that all negative, positive, and null results are equivalently captured in the analysis. The funnel plot indicates that there is limited publication bias in our analysis. However, we observe some substantial heterogeneity in the studies as shown by the range of distribution of the effect sizes. We can also note that a substantial number of studies fall out of the 95% confidence intervals implying that the null hypothesis for these studies having no effect would be rejected at 1% significance level. In addition, a substantial number of studies are right in the middle of the funnel plot (the dark-shaded part) report non-significant results. This might indicate that the asymmetry observed is potentially caused by something else other than publication bias. We are therefore more confident that there is limited publication bias in our analysis.

We also visualise the funnel plots for crop and non-crop technologies and show the results in supplementary Figure S9. We do not observe sufficient evidence of publication bias in studies of crop technologies. However, for non-crop technologies, we can observe the missing smaller studies on the non-significant side of the funnel plot. This might therefore suggest that a potential publication bias that non-significant studies were less likely to be published for non-crop technologies.

We also test another dimension of assessing publication bias by using Egger's test (Egger et al., 1997). For Egger's regression-based test, the null hypothesis of no publication bias, the intercept is expected to be zero (Egger et al., 1997; Lin & Chu, 2018). In Table 2, we observe that the test statistic for the presence of publication bias was significant.

Table 21: Egger's test for small sample publication bias

Particulars	Value
beta1	6.82
SE of beta1	1.01
z	6.77
Prob > |z|	0.00
H0	beta1 = 0 (No small-study effects)

Source: Author's computation (2023)

In Table 3 below, we implement the trip and fill method for adjusting for publication bias (Peters et al., 2007; Shi et al., 2019). We observe that even in the presence of imputing six studies, the mean effect size was still positive and significant.

Table 3: Non-Parametric trim and fill analysis for publication bias

Studies	Effect size	Lower CI	Upper CI
Observed	0.083	0.055	0.111
Observed + Imputed	0.057	0.023	0.092
Total number of studies	115		
Observed	109		
Imputed	6		

Source: Author's computation (2023)

4. Discussion and Conclusions

This review assesses the determinants of adoption and impacts of agricultural technologies and natural resource management practices in conflict and fragile settings. Our categorisation of countries affected by conflict and experiencing fragility was from the World Bank list of countries in conflict and fragile situations (World Bank, 2022). We then followed our pre-registered methodology and analysis plan[2] to conduct a literature search of published material on Scopus and Web of Science. We implement a systematic literature search following search terms from Rosenstock et al. (2015) and updating them with recent studies (Acevedo et al., 2020; Arslan et al., 2022; Piñeiro et al., 2020; Ruzzante et al., 2021) to establish a comprehensive literature search. All together, we accessed 42,024 materials for determinants and 35,970 materials for impact. As per our pre-registered analysis plan, we adopt a machine learning approach to select paper from the wide universe of materials accessed from the two databases. Machine learning is increasingly being adopted in literature reviews (Van Dijk et al., 2023) including studies that study agricultural technology adoption (Piñeiro et al., 2020). We use ASReview, which helps us to reduce the amount of time taken for human-aided literature scanning and selection (van de Schoot et al., 2021). The program implemented on the programming language Python, involves training the data using prior knowledge, for instance, that which is consistent with our search terms used in literature access, or expert knowledge or reviewing a smaller sample of papers. This creates training data which is then implemented on the full dataset. Through this process, we selected 500 papers for each of the determinants and impacts for a human-aided review process. We are therefore able to drop more than 98% of the material for review. After an additional human-aided review, we included 132 papers in the analysis of determinants and 39 papers were reviewed for the impact meta regression analysis.

4.1. Summary of the results

We observed an increasing number of studies both empirical and review studies that assess various dimensions of adoption of climate smart agricultural technologies and natural resource management practices. However, as was the purpose of this review, no reviews have so far been done with a focus on countries that are conflict stressed or facing climate change-induced fragility. The studies were highly dominated by two countries, namely Ethiopia and Nigeria, which together comprised of 85.6% of the studies reviewed. Moreover, we did not review a single paper from any of the countries listed as fragile due to climate change.[3]

Adoption of improved seeds, use of organic fertilizers and use of inorganic fertilizers were the most frequent technologies, and the least frequent technologies were contour farming, row planting, cover crop and mechanisation, and irrigation. The most adopted technologies were timely weeding (77%) and contour farming (67%) with while the least adopted was cover crop with an average adoption rate of only 11%. The mean adoption rate for all technologies was 50%.

[2] Our pre-registered methodology and analysis plan was posted on Open Science Foundation in February 2023 before data assessment commenced. It can be accessed on https://osf.io/zbxhk .

[3] These include Comoros, Kiribati, Marshall Islands, Federated States of Micronesia, Solomon Islands, Tuvalu and Papua New Guinea

Looking at the determinants of adoption, we categorised about 1400 listed determinants in 5 main groups, including household demographics, household resources, information and networks, biophysical characteristics, farm characteristics, crop characteristics and markets. Household demographics and household resources were the most common determinants. Determinants such as access to labour, household income and access to credit, and access to information, which have been previously identified in other reviews (Doss, 2006), were key factors identified in this review. Following on our descriptive review, we assessed the contribution of different characteristics by implementing Partial Correlation Coefficients and meta regressions.

First, the summary statistics for the Partial Correlation Coefficients show us the relative strength of each characteristic when all other characteristics are held at a constant (Mohr et al., 2021). We observed that almost all the characteristics identified had bidirectional relationship with adoption. This could potentially imply that where these are available, adoption would like increase but also in some instances, some characteristics could potentially act as substitutes to some technologies and hence inhibit adoption. However, the mean associations of access to mechanisation (Gebremeskel et al., 2018; Sertse et al., 2021; Verkaart et al., 2017) and availability of subsidies (Ngaiwi et al., 2023; Ouédraogo et al., 2017; Teklewold et al., 2019) had strong and positive association with adoption of technologies. On the other hand, the average association of household wealth/assets, access to information and risk perceptions including insurance premiums were more negative than positive. However, it seems that access to informal insurance is what drives the negative coefficients a lot more (Castellani & Viganò, 2017) though in some instances providing agriculture insurance through highly trusted informal insurance networks enhanced insurance uptake (Belissa et al., 2019). We also observe that for various types of technologies, predictor characteristics were well distributed except for insurance and other risk management technologies. Technologies such as agriculture insurance uptake remain an enigma in many low income countries (Kramer et al., 2022; Nshakira-Rukundo et al., 2021). It is therefore important to continue exploring these technologies, possibility with even more newer and potentially more trusted delivery channels and product structuring such as the picture based insurance (Ceballos et al., 2019) or multi-trigger insurance policies (Ndegwa et al., 2022) or risk contingent credit (Ndegwa et al., 2020; Shee et al., 2019). These products might offer farmers in conflict and fragile situations with more options and thus potential uptake.

Regarding the overall observation of negative and positive directions of most characteristics, previous studies have considered vote counting methodologies to assess the extent to which a given characteristic exhibits a negative or positive direction regardless of the magnitude (Arslan et al., 2022). While this is another way of interpreting the strength of characteristics, the method does not account for how given characteristics interact with each other to influence adoption. We instead extend on the summary partial correlation coefficients to implement partial correlation coefficient regressions following other recent studies (Ogundari & Bolarinwa, 2018; Ruzzante et al., 2021). The partial correlation coefficients are therefore able to show more clearly how a given characteristic behaves while accounting for the presence of other characteristics. By and large, most of the characteristics had positive and significant association with uptake. However, given that household demographic variables and household resource outlays are the most often group of characteristics that appear in the literature, it is potentially of more value if policy makers in the agriculture and climate resilience space approach uptake through channels that improve knowledge and awareness and incentivise demand.

Our impact meta-analysis shows that the studies that are funnelled into our analysis had some heterogeneity but were to a large extent not with publication bias. We use funnel plots to show that studies and estimates analysed were to a large extent, symmetrically distributed, including on both the negative and positive as well as null results. None of the other reviews conduct a meta-analysis of impacts of adopting agricultural technologies. This study, is therefore, though focusing on countries in conflict and climate fragilities, is the first, to our knowledge, that conducts a meta-analysis with the evaluation of effect sizes of various technologies and group of technologies. We find that by and large, agricultural technologies had substantial positive effect sizes on households when adopted. We categorise our analysis by both crop technologies and non-crop technologies where crop technologies refer to improved and resilient seeds and non-crop technologies are the rest of the technologies applied on farms to improve productivity or protect soil fertility and curb erosion. We find that in all dimensions, the effect sizes were significantly different from zero and positive.

4.2. Deviations from pre-registered protocol

The first limitation we would like to point out is one regarding our data selection process that utilises machine learning. While machine learning techniques are evolving and improving and drastically improve on the labour-intensive literature selection, they are not yet 100% full proof (van de Schoot et al., 2021; Van Dijk et al., 2023). As mentioned by van de Schoot et al. (2021) the labour savings of reducing human aided data selection by 95% can also carry the risk of missing 5% relevant studies. We mitigate this by carrying out additional hand searches yielding an additional 21 studies for assessing determinants and five studies for assessing impact. So, while this is not an actual limitation to our work, we state is as a caveat that even machine learning aided literature selection still needs extensive training and complimenting with human-aided search process to improve the quality of the review.

Secondly, in our pre-registered protocol, we intended to assess two additional dimensions. First, we intended to assess studies across different countries based on the World Bank categorisation of conflict or institutional and social fragility (World Bank, 2022). However, our search process did not yield enough studies to aid this categorisation, especially given that over 85% of the studies reviewed were from Nigeria and Ethiopia, both facing medium to high conflict situations. The current analysis is therefore more representative of countries in conflict and fails to represent other fragile situations such as climate fragility. This is partly because conflict affected countries and climate fragile countries tend to be the same. Nonetheless, the gaps in understanding specificities of take up and effects in climate-stressed countries need a lot more attention.

Finally, this review relied only on literature from two main databases – Web of Science and Scopus. In the pre-registration, we had intended to also include grey literature from repositories and libraries of organisations working on agricultural sciences such as the International Food Policy Research Institute, The World Bank, ECONSTOR, SSRN and AgEcon Search. However, an initial search of two of the grey literature databases, AgEcon Search and SSRN did not yield any results. We therefore opted to maximise the potential of the two academic databases. The choice of these databases was purely for their comprehensive coverage and indexing of social science literature, including that covering agricultural and natural sciences and their previous use in related studies. Moreover, Web of Science and Scopus tend to perform excellently when researchers are interested only in published material (Martín-Martín et al., 2018; Pranckutė, 2021).

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Supplementary material

Key search terms for technologies

1. Adoption

Adoption OR adopt OR “take up” OR “take-up” OR uptake OR “up-take” OR use OR embrace OR determinants OR determine OR participation OR participate OR factors OR diffuse OR diffusion

2. Soil fertility (natural) management techniques

“Organic farming” OR “Manure” OR “organic fertili$ers” OR “Mulching” OR “Crop residue” OR “Poultry manure” OR “Livestock manure” OR Straw OR Trash OR biomas OR intercropping OR agroforestry OR “agro-forestry” OR “crop rotation” OR “shallow planting” OR “early transplanting” OR “sparse planting” OR “Polyculture”

3. Erosion management techniques

“contour hedgerows” OR “terracing” OR “rock bunds” OR “soil bunds” OR “soil cover” OR mulching OR “zero tillage” OR “conservation tillage” OR “minimum tillage” OR “tilling” OR tillage OR “conservation farming” OR “conservation agriculture”

4. Farm inputs

seed* OR “hybrid varieties” OR “hybrid seeds” OR “improved variet*” OR “improved seed*” OR “drought toleran*” OR “pest resist*” OR “genetically modified” OR GMO OR Biotechnolog* OR “Bio-technolog*” OR “high yielding” OR cultivar OR “climate resilien*” OR “drought resistan*” OR “heat toleran*” OR “stress toleran*” OR “Water saving” OR “Salinity resistan*” OR “Salinity toleran*” OR “inorganic” OR “fertili$ers” OR “agro-chemical*” OR agrochemical OR pesticide OR herbicide

5. risk reduction and mitigation

insurance or “agro-insurance” OR “climate insurance” OR “weather insurance” OR “index insurance” OR “index-based insurance” OR “multi-year area-based insurance” OR “agricultur* insurance” OR “rainfall insurance” OR “pest insurance” OR “climate insurance” OR “drought insurance” OR “climate risk insurance” OR “agricultur* risk insurance”

6. mechanisation

mechanisation OR tractor* OR “groundwater pump” OR thresher OR harvester OR “treadle pump” OR “laser-land” OR “grain storage” OR “Improved drying techniques” OR “Improved preservation” OR “Improved physical storage” OR “Changing harvest time” OR “Alternate harvesting techniques” OR “intermittent irrigation” OR “groundwater” OR “ground water” OR “drip irrigation” OR “water harvest*” OR “water storage” OR “deficit irrigation” OR zai OR zay OR “zone irrigation” OR “system of rice intensification” OR “alternate wetting and drying” OR “micro-dosing” OR microdosing OR “micro dosing” OR “precision agriculture”

Outcomes

- Productivity

Yield OR “Yield stability” OR Output OR Outturn OR Product OR Efficien* OR Productivity

- Income

Income OR Revenue OR Wealth OR Earnings OR Profit* OR Return*

- Food security

Consumption OR “Food access” OR “Food security” OR “Food intake” OR “Food expenditure” OR “Food availability” OR “Dietary diversity” OR “HDDS” OR IDDS OR MDDS OR “Nutrition” OR “Nutrition* security” OR Malnutrition OR Undernutrition OR Undernourishment OR Calorie OR “Kilocalorie*” OR “kilo calories” OR “Food scarci”

- Environmental sustainability

“Soil quality” OR “Water quality” OR Biodiversity OR “Land degrad*” OR Conservation OR “Greenhouse gases”

- Effect/ impact

Effect* OR Impact*

- Study designs

“treatment group” OR “control group” OR exposed OR treatment OR control OR “comparison group” OR "field experiment” OR “experimental group” OR "quasi-experimental" OR "quasi experimental" OR "randomi$ed controlled trial" OR rct OR "difference-in-difference*" OR "difference in difference*" OR "instrumental variables" OR "regression discontinuity" OR "endogenous switching" OR “panel data” OR “fixed effects” OR “first difference”

- Conflict OR violence OR fragility OR “fragile settings” OR “violent conflict” OR “war” OR “armed conflict” OR “crisis”

List of Fragile and Conflict Affected Countries

Afghanistan OR Armenia OR Azerbaijan OR “Burkina Faso” OR Burundi OR Cameroon OR “Central African Republic” OR Chad OR Comoros OR “Democratic Republic of Congo” OR “Republic of Congo” OR Eritrea OR Ethiopia OR “Guinea-Bissau” OR Haiti OR Iraq OR Kiribati OR Kosovo OR Lao PDR OR Laos OR Lebanon OR Liberia OR Libya OR Madagascar OR Mali OR “Marshall Islands” OR Micronesia OR Mozambique OR Myanmar OR Burma OR Nepal OR Niger OR Nigeria OR “Papua New Guinea” OR “Sao Tome and Principe” OR “Sierra Leone” OR “Solomon Islands” OR Somalia OR “South Sudan” OR Sudan OR “Syrian Arab Republic” OR Syria OR “Timor-Leste” OR Tonga OR Tuvalu OR Vanuatu OR Venezuela OR “West Bank” OR Gaza OR Palestine OR Yemen OR Zimbabwe

Supplementary Tables and Figures

Table S2: Overview of existing reviews

	Systematic literature selection	Thematic coverage	Methodological focus	Outcome focus	Geographical focus
Piñeiro et al. (2020)	Yes	General	Descriptive	Determinants	General
Acevedo et al. (2020)	Yes	Climate-resilient crops	Descriptive	Determinants	General/low- and middle-income countries
Ahmad et al. (2020)	Yes	Erosion control practices	Descriptive	Determinants	Asia
Stathers et al. (2020)	Yes	Post-harvest loss reduction	Meta analysis	Determinants	Sub-Saharan Africa and Asia
Takahashi et al. (2020)	No	General	Descriptive	Determinants and impacts	Sub-Saharan Africa
Ruzzante et al. (2021)	No	General	Meta analysis	Determinants	General
Arslan et al. (2022)	Yes	General	Meta analysis	Determinants	Sub-Saharan Africa
Oyetunde-Usman (2022)	No	General	Descriptive	Determinants	East and West Africa
Suri & Udry (2022)	No	General	Descriptive	Determinants	Africa
Schulz & Börner (2023)	Yes	General	Meta analysis	Determinants	General

Source: Own elaboration (2023).

Table S2: Estimates from the multivariate Partial Correlation Coefficients Meta-analysis Model

Characteristic	Coefficient estimate	Standard Error	z-value	p-value	Lower bound	Upper bound	Signi-ficance
assets/wealth	0.147	0.041	3.630	0.0003	0.068	0.226	***
credit	0.164	0.040	4.104	<.0001	0.086	0.242	***
crop choice	0.130	0.054	2.412	0.0159	0.024	0.236	*
distance to land	0.075	0.047	1.591	0.1116	-0.018	0.168	
distance to markets	0.052	0.039	1.331	0.1832	-0.025	0.130	
education	0.216	0.036	5.990	<.0001	0.145	0.288	***
experience	0.196	0.049	4.014	<.0001	0.101	0.292	***
extension services	0.214	0.037	5.852	<.0001	0.143	0.286	***
farm management	0.201	0.044	4.520	<.0001	0.114	0.288	***
fertilizers	0.166	0.048	3.473	0.0005	0.072	0.259	***
gender	0.137	0.042	3.286	0.001	0.055	0.219	**
household size	0.195	0.037	5.295	<.0001	0.123	0.267	***
income	0.191	0.038	5.022	<.0001	0.116	0.265	***
information	**0.245**	0.045	5.429	<.0001	0.157	0.334	***
insurance, risk & perceptions	**0.337**	0.062	5.408	<.0001	0.215	0.459	***
labour	0.206	0.053	3.890	<.0001	0.102	0.309	***
land	0.172	0.036	4.843	<.0001	0.103	0.242	***
land elevation	0.100	0.048	2.100	0.0357	0.007	0.193	*
livestock	0.178	0.039	4.504	<.0001	0.100	0.255	***
markets	0.130	0.050	2.586	0.0097	0.032	0.229	**
mechanization	**0.269**	0.044	6.094	<.0001	0.182	0.355	***
other	0.159	0.073	2.169	0.0301	0.015	0.303	*
region	0.068	0.039	1.736	0.0826	-0.009	0.144	.
seeds	**0.268**	0.052	5.161	<.0001	0.166	0.370	***
social networks	0.218	0.037	5.833	<.0001	0.145	0.291	***
soil features	0.199	0.037	5.346	<.0001	0.126	0.272	***
subsidies	**0.284**	0.099	2.886	0.0039	0.091	0.477	**
weather	0.155	0.041	3.820	0.0001	0.075	0.234	***
yield	**0.260**	0.051	5.087	<.0001	0.160	0.361	***

Source: Own elaboration form model results (2023).

N= 1062. Significance levels correspond with ***1%, **5% and *10%.

Table S 3: Meta-analysis table for overall effect of agricultural technologies

Study	Effect size	[95% conf.	interval]	% weight
Group: Crop technology				
Abate et al.(2018)	0.09	0.002	0.179	0.69
Abdoulaye et al. (2018)	0.058	0.013	0.103	0.77
Abdoulaye et al. (2018)	0.08	0.035	0.125	0.77
Abdoulaye et al. (2018)	0.086	0.041	0.131	0.77
Abdoulaye et al. (2018)	-0.075	-0.12	-0.03	0.77
Assaye et al. (2022)	-0.138	-0.218	-0.057	0.7
Assaye et al. (2022)	0.194	0.113	0.275	0.7
Assaye et al. (2022)	0.117	0.036	0.197	0.7
Assaye et al. (2022)	-0.087	-0.168	-0.007	0.71
Aweke et al. (2021)	0.139	0.014	0.264	0.6
Aweke et al. (2021)	0.176	0.051	0.301	0.6
Awotide et al. (2016)	0.081	0.001	0.162	0.71
Dontsop Nguezet et al. (2012)	0.02	-0.068	0.108	0.69
Etana et al. (2020)	0.415	0.343	0.487	0.72
Etana et al. (2020)	0.07	0.001	0.139	0.73
Etana et al. (2020)	0.086	0.017	0.155	0.73
Gautam et al. (2020)	0.007	-0.062	0.077	0.73
Gautam et al. (2020)	0.16	0.09	0.23	0.73
Gautam et al. (2020)	-0.026	-0.096	0.043	0.73
Hailu & Mezegebo (2021)	0.006	-0.093	0.105	0.66
Jaleta et al. (2018)	0.134	0.086	0.181	0.77
Jaleta et al. (2018)	0.054	0.007	0.101	0.77
Jaleta et al. (2018)	-0.048	-0.095	-0.001	0.77
Jaleta et al. (2018)	0.099	0.052	0.145	0.77
Kassie et al. (2018)	0.27	0.227	0.313	0.77
Kassie et al. (2018)	0.046	0.004	0.089	0.77
Kassie et al. (2018)	0.065	0.023	0.108	0.77
Makate et al. (2017)	0.079	-0.001	0.159	0.71
Makate et al. (2017)	0.166	0.086	0.247	0.71
Makate et al. (2017)	0.127	0.047	0.207	0.71
Makate et al. (2017)	0.106	0.026	0.186	0.71
Makate et al. (2019)	0.105	0.025	0.185	0.71
Makate et al. (2019)	0.06	-0.02	0.14	0.71
Makate et al. (2019)	-0.04	-0.12	0.04	0.71
Makate et al. (2019)	0.129	0.049	0.21	0.71
Makate et al. (2019)	0.089	0.009	0.169	0.71
Makate et al. (2019)	0.153	0.073	0.234	0.71
Makate et al. (2019)	0.111	0.031	0.191	0.71
Makate et al. (2019)	0.05	-0.03	0.13	0.71

Makate et al. (2019)	-0.016	-0.096	0.064	0.71
Makate et al. (2019)	0.146	0.066	0.226	0.71
Makate et al. (2019)	-0.017	-0.097	0.063	0.71
Makate et al. (2019)	0.036	-0.044	0.116	0.71
Manda et al. (2019)	0.193	0.142	0.244	0.76
Manda et al. (2019)	0.132	0.081	0.182	0.76
Olagunju et al. (2020)	0.068	0.027	0.109	0.78
Olagunju et al. (2020)	0.075	0.034	0.116	0.78
Olagunju et al. (2020)	0.035	-0.006	0.075	0.78
Olagunju et al. (2020)	0.058	0.017	0.099	0.78
Olagunju et al. (2020)	0.013	-0.028	0.054	0.78
Olagunju et al. (2020)	0.073	0.032	0.113	0.78
Olagunju et al. (2020)	0.049	0.008	0.089	0.78
Olagunju et al. (2020)	0.02	-0.021	0.061	0.78
Olagunju et al. (2020)	0.065	0.024	0.106	0.78
Olagunju et al. (2020)	0.055	0.014	0.096	0.78
Olagunju et al. (2020)	0.029	-0.012	0.07	0.78
Olagunju et al. (2020)	0.048	0.007	0.089	0.78
Olagunju et al. (2020)	0.078	0.037	0.119	0.78
Olagunju et al. (2020)	0.009	-0.032	0.05	0.78
Olagunju et al. (2020)	0.082	0.041	0.123	0.78
Oyinbo et al. (2019)	0.188	0.107	0.269	0.7
Oyinbo et al. (2019)	0.22	0.139	0.301	0.7
Oyinbo et al. (2019)	0.233	0.152	0.314	0.7
Oyinbo et al. (2019)	0.241	0.16	0.322	0.7
Oyinbo et al. (2019)	0.262	0.181	0.343	0.7
Oyinbo et al. (2019)	0.207	0.126	0.287	0.7
Verkaart et al. (2017)	0.093	0.013	0.173	0.71
Zegeye (2021)	0.025	-0.049	0.1	0.72
Zegeye (2021)	0.135	0.06	0.21	0.72
Zegeye et al. (2022)	-0.258	-0.299	-0.216	0.77
theta	0.081	0.058	0.104	
Group: Non-crop technology				
Adhikari et al. (2018)	0.287	0.105	0.47	0.47
Gebru et al. (2020)	0.686	0.513	0.858	0.49
Habtewold (2021)	-0.043	-0.08	-0.006	0.78
Michler et al. (2019)	-0.026	-0.096	0.044	0.73
Michler et al. (2019)	-0.041	-0.112	0.029	0.73
Michler et al. (2019)	-0.007	-0.077	0.063	0.73
Michler et al. (2019)	-0.089	-0.16	-0.019	0.73
Michler et al. (2019)	-0.036	-0.106	0.035	0.73
Teklewold et al. (2017)	0.205	0.177	0.234	0.79
Teklewold et al. (2017)	0.06	0.031	0.088	0.79

Teklewold et al. (2017)	0.238	0.209	0.267	0.79
Tesfay (2020)	0.458	0.375	0.54	0.7
Tesfay (2020)	0.096	0.017	0.174	0.71
Tesfay (2020)	0.103	0.024	0.181	0.71
Tesfay (2020)	0.083	0.004	0.161	0.71
Wong et al. (2020)	-0.002	-0.06	0.056	0.75
Wong et al. (2020)	-0.019	-0.076	0.039	0.75
Wong et al. (2020)	0.021	-0.037	0.079	0.75
Wong et al. (2020)	0.009	-0.048	0.067	0.75
Wong et al. (2020)	0.005	-0.053	0.062	0.75
Wong et al. (2020)	-0.049	-0.107	0.009	0.75
Wong et al. (2020)	0.009	-0.049	0.067	0.75
Wong et al. (2020)	-0.024	-0.081	0.034	0.75
Wong et al. (2020)	-0.035	-0.092	0.023	0.75
Wong et al. (2020)	0.052	-0.006	0.11	0.75
Wong et al. (2020)	0.025	-0.033	0.083	0.75
Wong et al. (2020)	-0.034	-0.092	0.024	0.75
Wong et al. (2020)	0.1	0.042	0.158	0.75
Wong et al. (2020)	-0.04	-0.098	0.017	0.75
Wong et al. (2020)	0.082	0.024	0.14	0.75
Wong et al. (2020)	0.002	-0.056	0.059	0.75
Wong et al. (2020)	-0.008	-0.066	0.05	0.75
Wong et al. (2020)	0.069	0.011	0.126	0.75
Wong et al. (2020)	-0.029	-0.086	0.029	0.75
Wong et al. (2020)	0.023	-0.035	0.08	0.75
Wong et al. (2020)	-0.017	-0.075	0.04	0.75
Wong et al. (2020)	0.055	-0.003	0.112	0.75
Wong et al. (2020)	0.061	0.003	0.119	0.75
Wong et al. (2020)	0.002	-0.056	0.06	0.75
Wong et al. (2020)	-0.022	-0.08	0.036	0.75
Wong et al. (2020)	0.03	-0.028	0.087	0.75
Wong et al. (2020)	-0.063	-0.121	-0.005	0.75
Wong et al. (2020)	-0.073	-0.131	-0.016	0.75
Wong et al. (2020)	0.044	-0.014	0.101	0.75
Wong et al. (2020)	-0.036	-0.094	0.021	0.75
Wong et al. (2020)	0.054	-0.004	0.111	0.75
Wong et al. (2020)	0.03	-0.028	0.088	0.75
Wong et al. (2020)	-0.009	-0.067	0.048	0.75
Wong et al. (2020)	-0.002	-0.06	0.056	0.75
Wong et al. (2020)	0.024	-0.034	0.082	0.75
Wong et al. (2020)	0.022	-0.035	0.08	0.75
Wong et al. (2020)	0.028	-0.03	0.086	0.75
Wong et al. (2020)	-0.028	-0.086	0.03	0.75
Wong et al. (2020)	-0.011	-0.069	0.047	0.75
Wong et al. (2020)	0.001	-0.057	0.058	0.75

Yitbarek & Tesfaye (2022)	0.077	0.038	0.117	0.78
Yitbarek & Tesfaye (2022)	0.034	-0.005	0.073	0.78
Yitbarek & Tesfaye (2022)	0.055	0.016	0.094	0.78
Yitbarek & Tesfaye (2022)	0.035	-0.004	0.075	0.78
Zeweld et al. (2020)	0.398	0.289	0.506	0.64
Zeweld et al. (2020)	0.577	0.463	0.69	0.63
Zeweld et al. (2020)	0.315	0.208	0.422	0.64
Zeweld et al. (2020)	0.226	0.12	0.332	0.65
Zeweld et al. (2020)	0.213	0.107	0.319	0.65
Zeweld et al. (2020)	0.326	0.219	0.434	0.64
Zeweld et al. (2020)	0.197	0.091	0.303	0.65
Zeweld et al. (2020)	0.159	0.054	0.264	0.65
theta	0.065	0.033	0.097	
Overall theta	0.073	0.053	0.092	

Source: Own elaboration form model results (2023).

Partial Correlation Coefficients by Technology Type

Figure S 1: Partial Correlation Coefficients for Soil Fertility Management

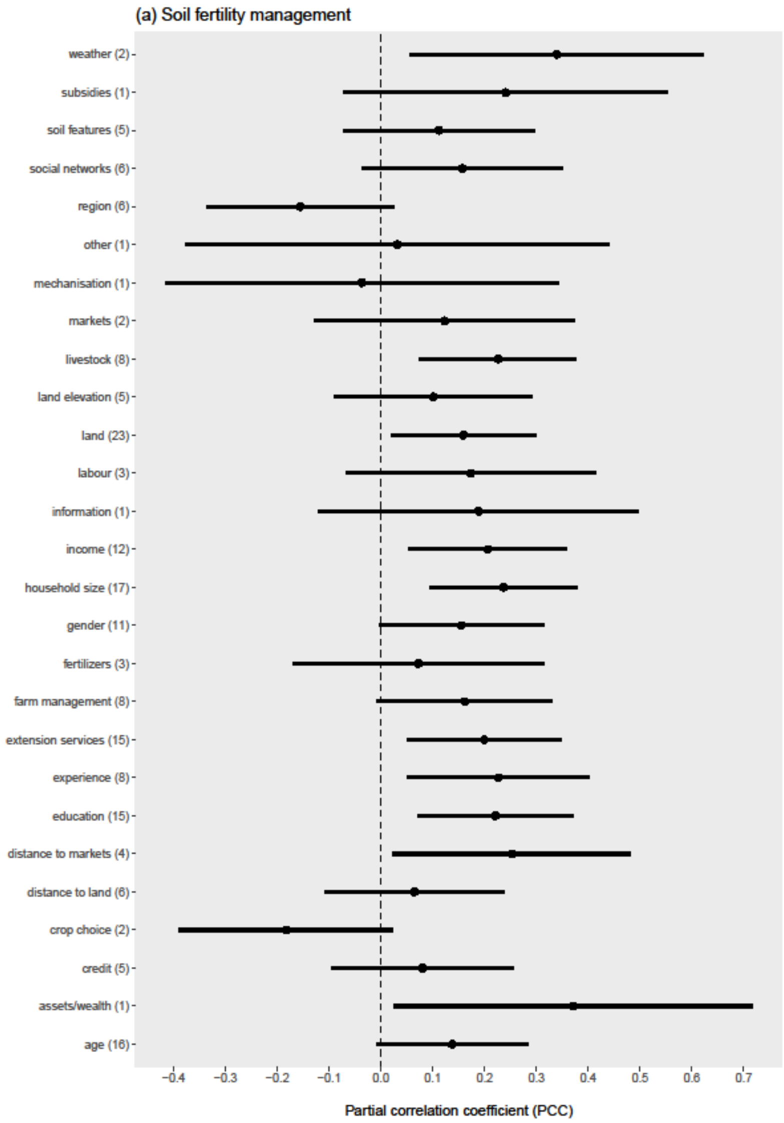

Figure S 2: Partial Correlation Coefficients for Erosion Management

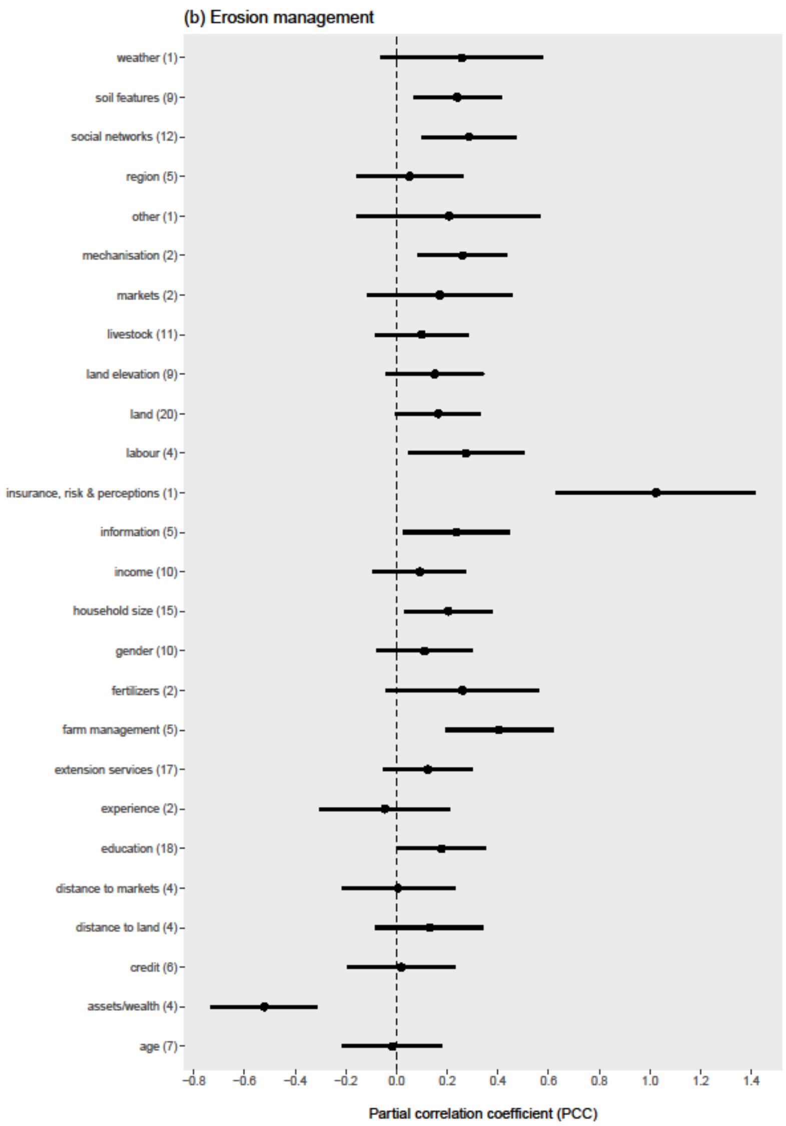

Figure S 3: Partial Correlation Coefficients for Inputs

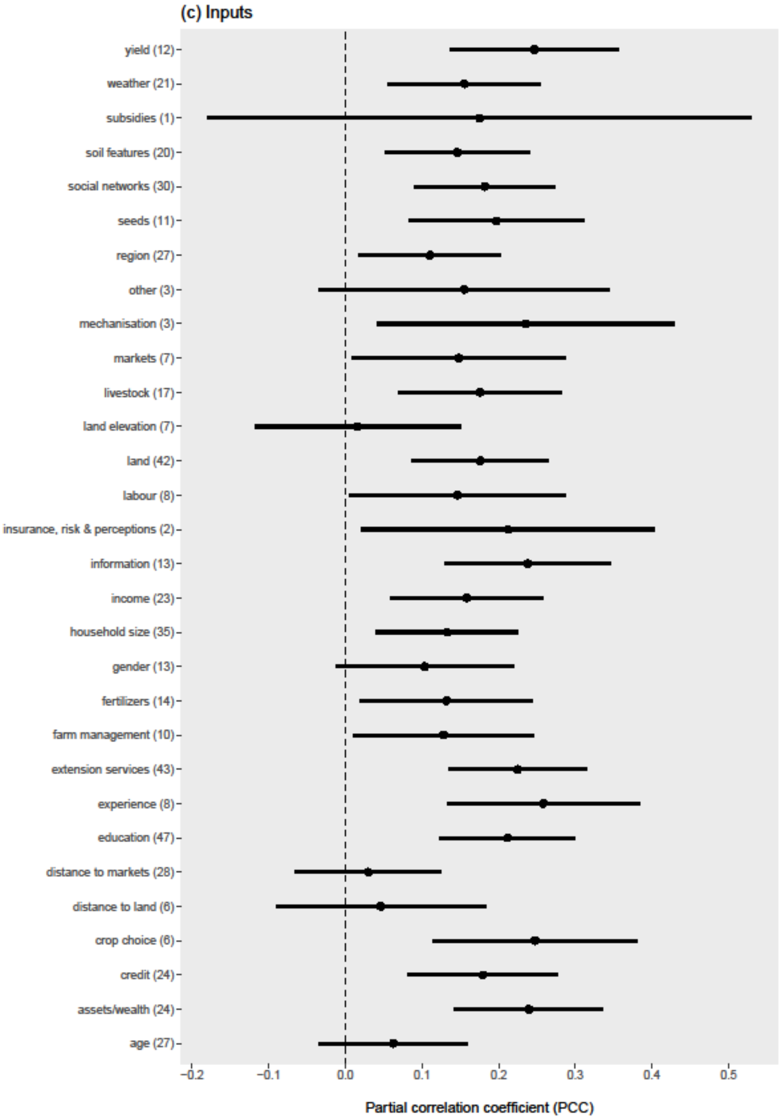

Figure S 4: Partial Correlation Coefficients for Insurance

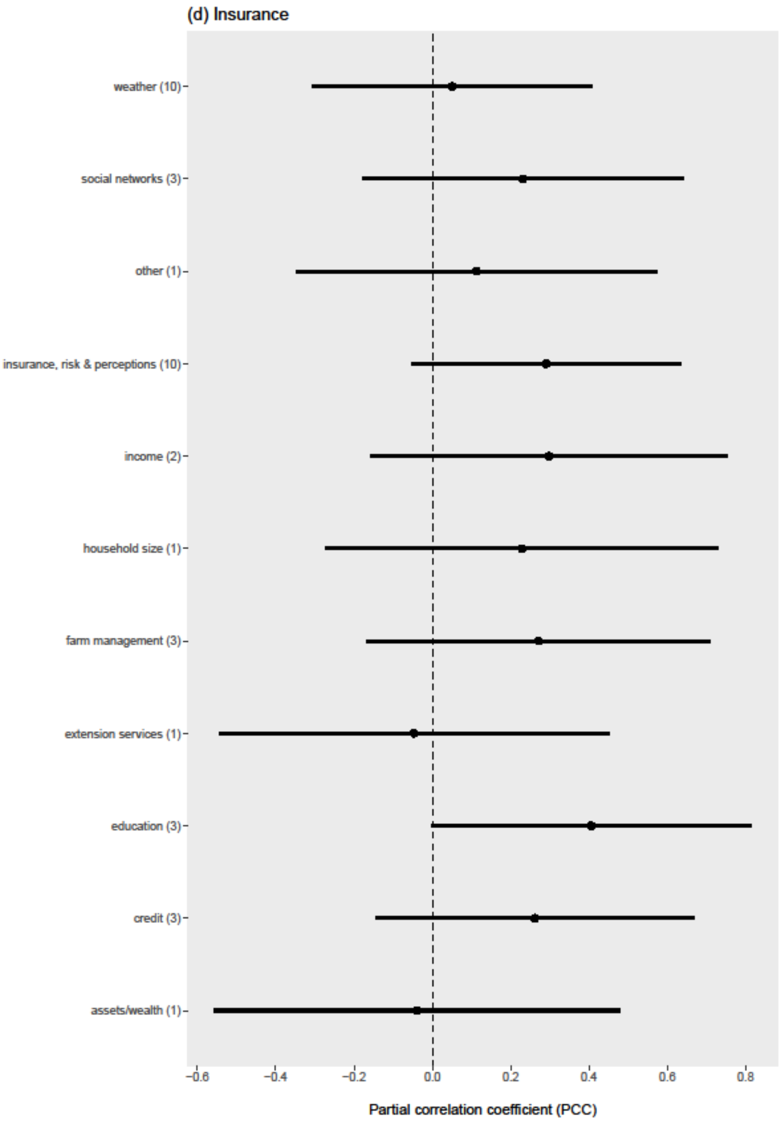

Figure S 5: Partial Correlation Coefficients for Mechanisation

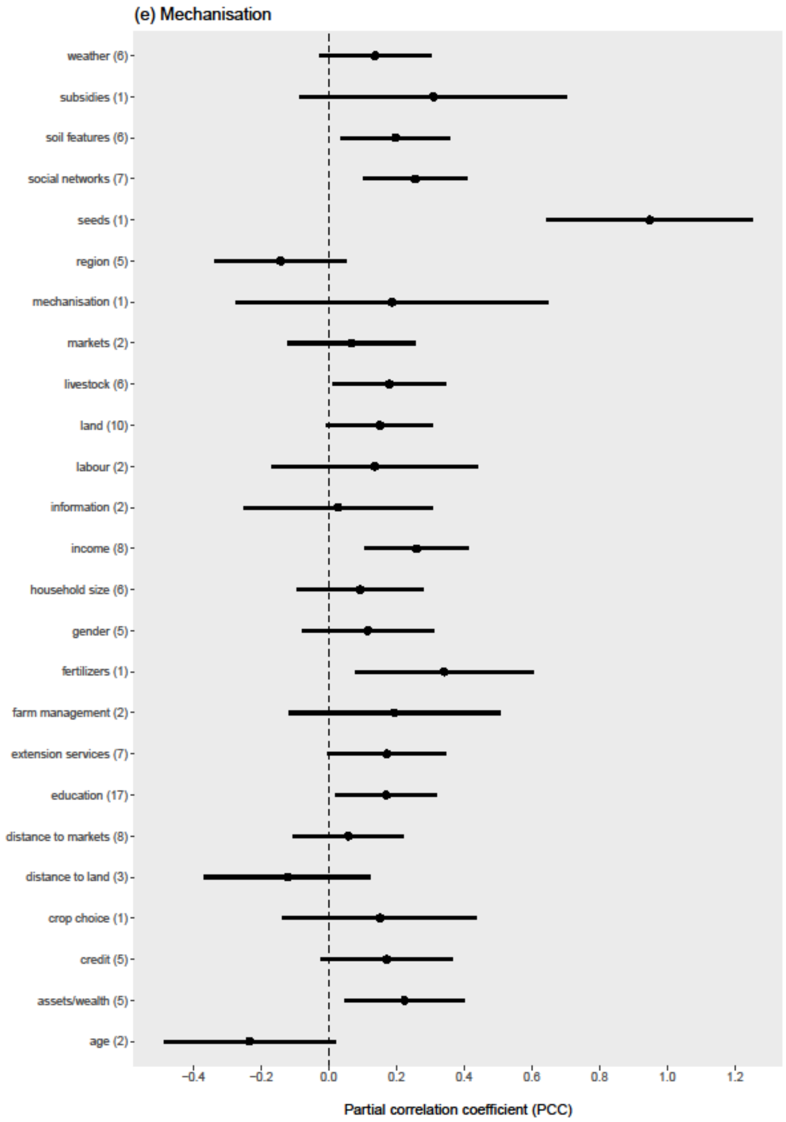

Figure S 6: Forest plot for technologies assessing impacts on farm productivity.

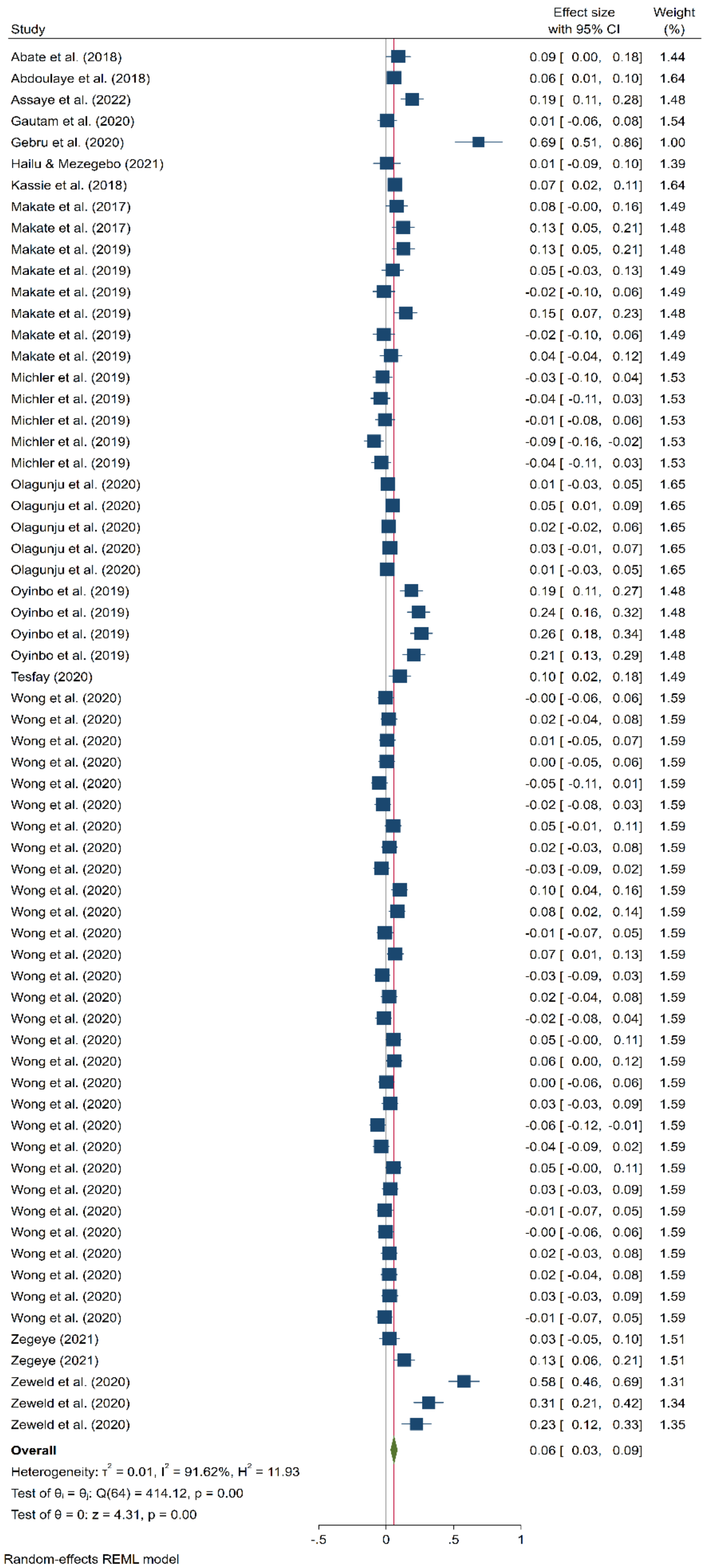

Figure S 7: Forest plot for technologies assessing effects on household food security

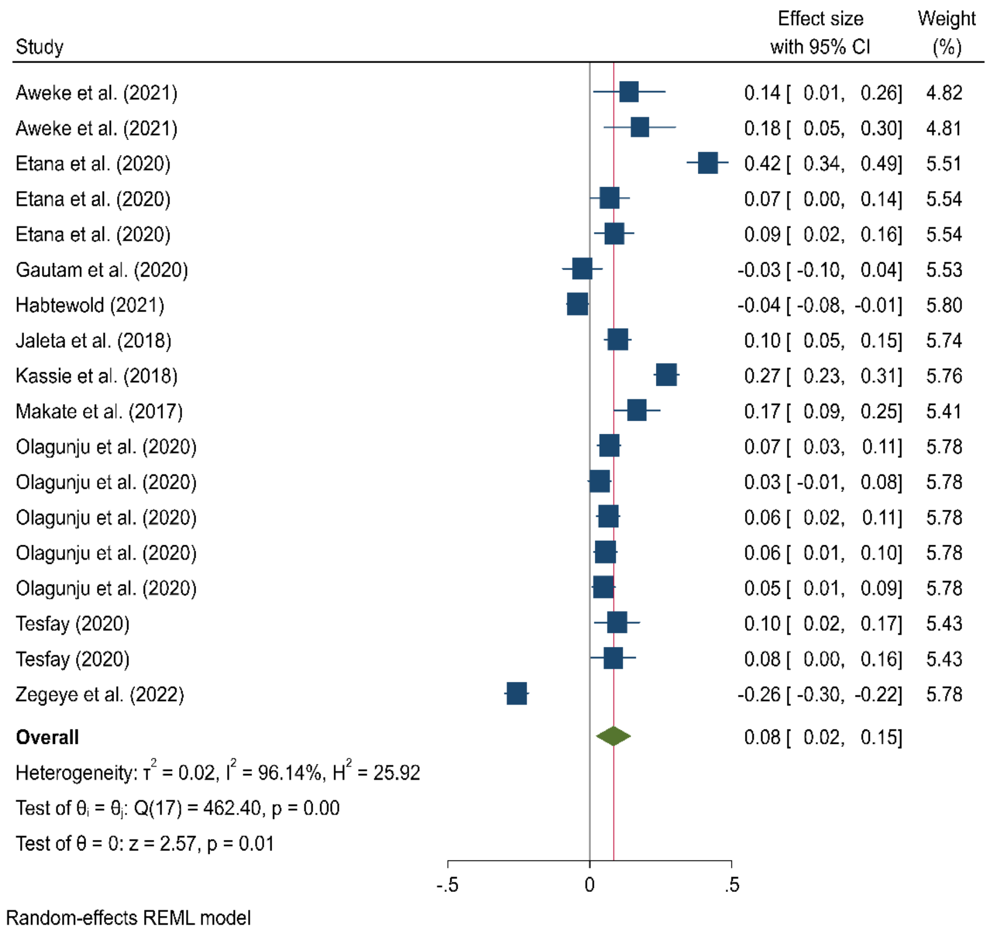

Figure S 8: Forest plot for technologies assessing household welfare

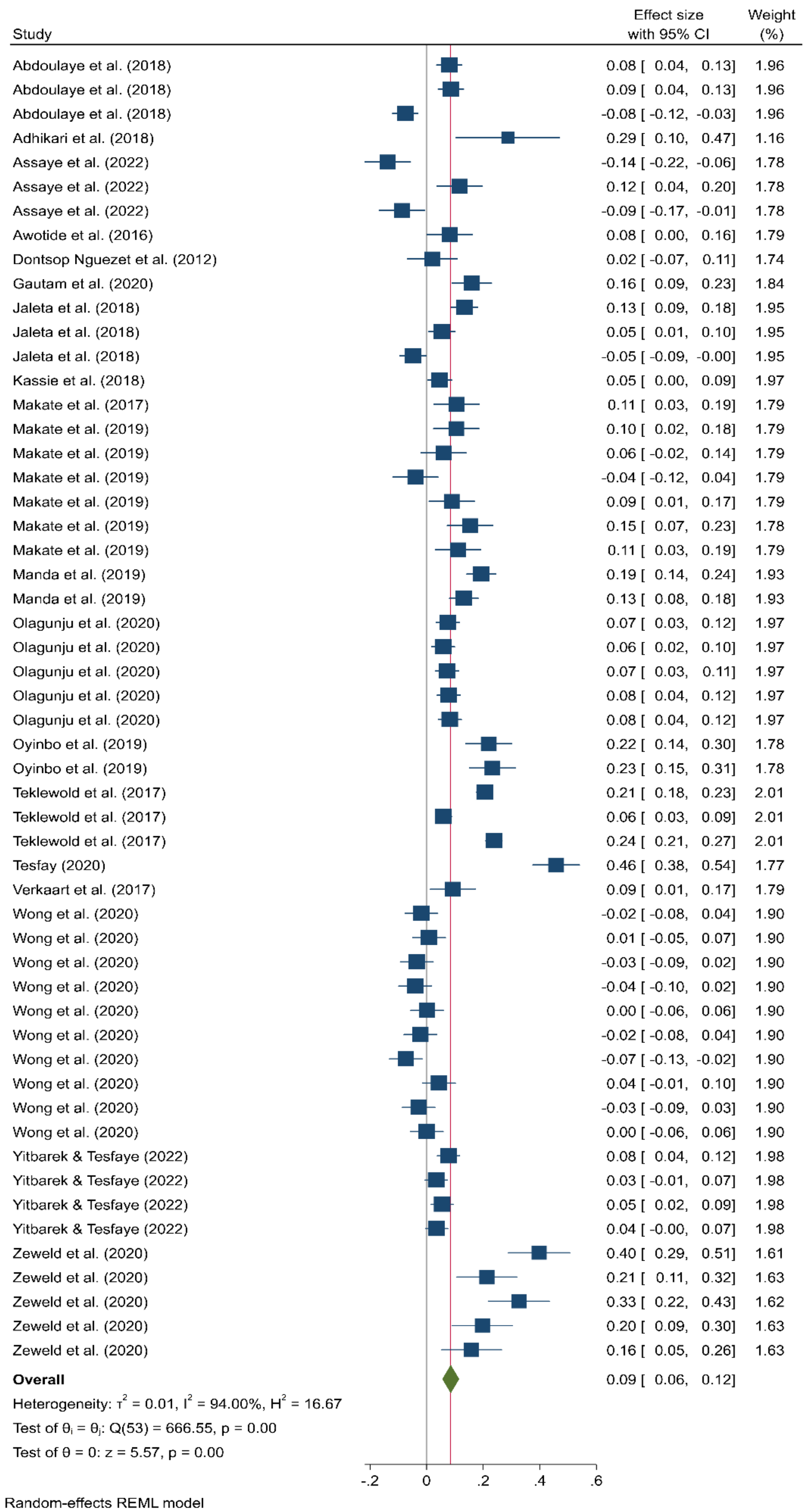

Figure S 9: Funnel plots by crop and non-crop technology

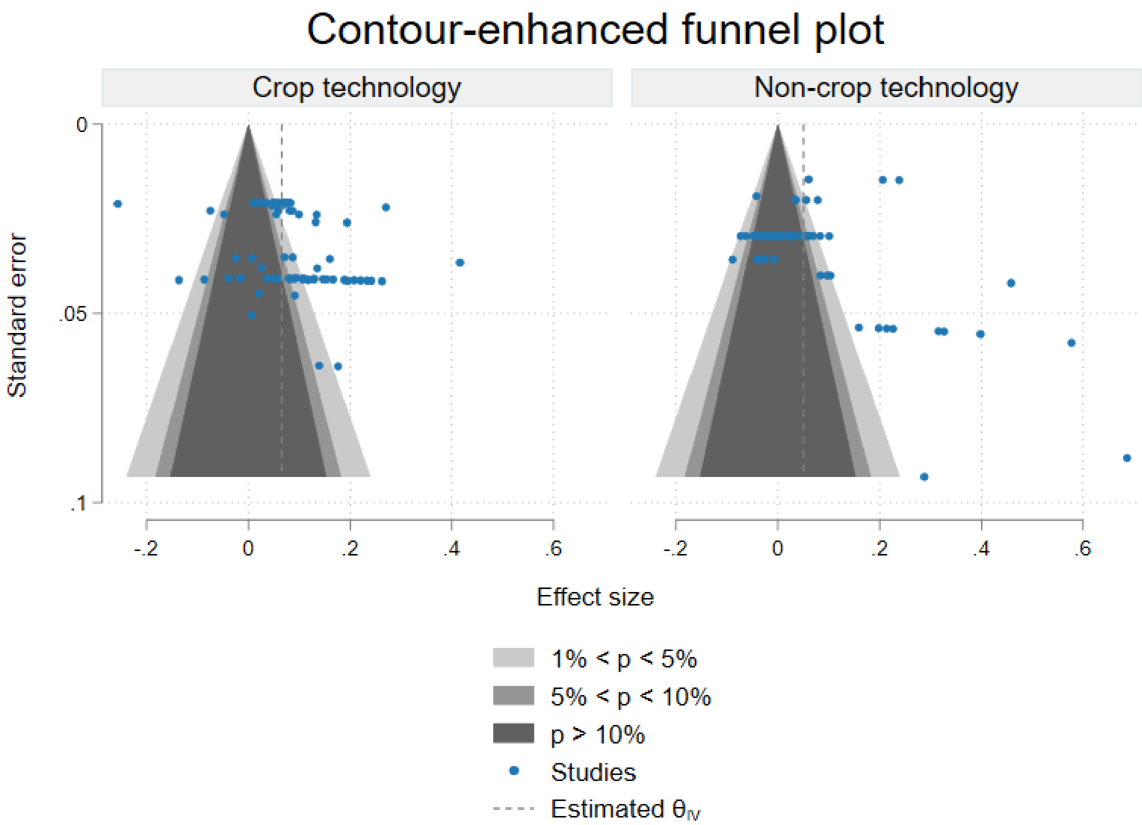

Figure S 10: Overall meta regression using the DerSimonian–Laird method for comparison with the Random Effects Maximum Likelihood (REML) method used in the main results.

Study	Effect size	Lower CI	Upper CI	% weight
Manda et al. (2019)	0.132	0.081	0.182	0.960
Manda et al. (2019)	0.193	0.142	0.244	0.960
Zegeye (2021)	0.025	-0.049	0.100	0.910
Zegeye (2021)	0.175	0.100	0.250	0.910
Zegeye (2021)	0.135	0.060	0.210	0.910
Makate et al. (2019)	0.105	0.025	0.185	0.900
Makate et al. (2019)	0.060	-0.020	0.140	0.900
Makate et al. (2019)	0.036	-0.044	0.116	0.900
Makate et al. (2019)	0.153	0.073	0.234	0.900
Makate et al. (2019)	0.146	0.066	0.226	0.900
Makate et al. (2019)	-0.017	-0.097	0.063	0.900
Makate et al. (2019)	0.050	-0.030	0.130	0.900
Makate et al. (2019)	0.089	0.009	0.169	0.900
Michler et al. (2019)	-0.041	-0.112	0.029	0.920
Michler et al. (2019)	-0.036	-0.106	0.035	0.920
Michler et al. (2019)	-0.026	-0.096	0.044	0.920
Michler et al. (2019)	-0.089	-0.160	-0.019	0.920
Michler et al. (2019)	-0.007	-0.077	0.063	0.920
Makate et al. (2017)	0.127	0.047	0.207	0.900
Zegeye et al. (2022)	-0.258	-0.299	-0.216	0.980
Abate et al. (2018)	0.090	0.002	0.179	0.880
Gebru et al. (2020)	0.686	0.513	0.858	0.640
Assaye et al. (2022)	0.153	0.073	0.234	0.900
Zeweld et al. (2020)	0.577	0.463	0.690	0.810
Zeweld et al. (2020)	0.197	0.091	0.303	0.830
Zeweld et al. (2020)	0.213	0.107	0.319	0.830
Zeweld et al. (2020)	0.315	0.208	0.422	0.820
Zeweld et al. (2020)	0.326	0.219	0.434	0.820
Zeweld et al. (2020)	0.226	0.120	0.332	0.830
Zeweld et al. (2020)	0.159	0.054	0.264	0.830
Zeweld et al. (2020)	0.398	0.289	0.506	0.820
Olagunju et al. (2020)	0.049	0.008	0.089	0.980
Abate et al. (2018)	0.089	0.002	0.177	0.880
Gautam et al. (2020)	-0.026	-0.096	0.043	0.920
Gautam et al. (2020)	0.160	0.090	0.230	0.920
Gautam et al. (2020)	0.007	-0.062	0.077	0.920
Verkaart et al. (2017)	0.093	0.013	0.173	0.900
Wong et al. (2020)	-0.019	-0.076	0.039	0.950
Wong et al. (2020)	0.021	-0.037	0.079	0.950
Wong et al. (2020)	0.061	0.003	0.119	0.950
Wong et al. (2020)	0.069	0.011	0.126	0.950
Wong et al. (2020)	0.025	-0.033	0.083	0.950
Wong et al. (2020)	0.100	0.042	0.158	0.950

Wong et al. (2020)	0.055	-0.003	0.112	0.950
Wong et al. (2020)	0.022	-0.035	0.080	0.950
Wong et al. (2020)	-0.063	-0.121	-0.005	0.950
Wong et al. (2020)	-0.029	-0.086	0.029	0.950
Wong et al. (2020)	-0.002	-0.060	0.056	0.950
Wong et al. (2020)	-0.017	-0.075	0.040	0.950
Wong et al. (2020)	0.024	-0.034	0.082	0.950
Wong et al. (2020)	0.002	-0.056	0.060	0.950
Wong et al. (2020)	-0.028	-0.086	0.030	0.950
Wong et al. (2020)	0.028	-0.030	0.086	0.950
Wong et al. (2020)	-0.009	-0.067	0.048	0.950
Wong et al. (2020)	0.023	-0.035	0.080	0.950
Wong et al. (2020)	0.009	-0.049	0.067	0.950
Wong et al. (2020)	0.005	-0.053	0.062	0.950
Wong et al. (2020)	0.052	-0.006	0.110	0.950
Wong et al. (2020)	-0.036	-0.094	0.021	0.950
Wong et al. (2020)	-0.073	-0.131	-0.016	0.950
Wong et al. (2020)	0.054	-0.004	0.111	0.950
Wong et al. (2020)	0.002	-0.056	0.059	0.950
Wong et al. (2020)	-0.002	-0.060	0.056	0.950
Wong et al. (2020)	0.001	-0.057	0.058	0.950
Wong et al. (2020)	-0.035	-0.092	0.023	0.950
Wong et al. (2020)	-0.008	-0.066	0.050	0.950
Wong et al. (2020)	-0.034	-0.092	0.024	0.950
Wong et al. (2020)	-0.011	-0.069	0.047	0.950
Wong et al. (2020)	0.030	-0.028	0.088	0.950
Wong et al. (2020)	0.030	-0.028	0.087	0.950
Wong et al. (2020)	-0.049	-0.107	0.009	0.950
Wong et al. (2020)	-0.022	-0.080	0.036	0.950
Wong et al. (2020)	-0.024	-0.081	0.034	0.950
Wong et al. (2020)	0.009	-0.048	0.067	0.950
Wong et al. (2020)	0.082	0.024	0.140	0.950
Wong et al. (2020)	-0.040	-0.098	0.017	0.950
Wong et al. (2020)	0.044	-0.014	0.101	0.950
Hailu & Mezegebo (2021)	0.006	-0.093	0.105	0.850
Adhikari et al. (2018)	0.287	0.105	0.470	0.610
Yitbarek & Tesfaye (2022)	0.055	0.016	0.094	0.980
Yitbarek & Tesfaye (2022)	0.034	-0.005	0.073	0.980
Yitbarek & Tesfaye (2022)	0.077	0.038	0.117	0.980
Yitbarek & Tesfaye (2022)	0.035	-0.004	0.075	0.980
Awotide et al. (2016)	0.216	0.135	0.297	0.900
Awotide et al. (2016)	-0.099	-0.179	-0.019	0.900
Awotide et al. (2016)	0.081	0.001	0.161	0.900
Kassie et al. (2018)	0.120	0.077	0.162	0.980
Kassie et al. (2018)	0.046	0.004	0.089	0.980
Abdoulaye et al. (2018)	-0.075	-0.120	-0.030	0.970

Abdoulaye et al. (2018)	0.058	0.013	0.103	0.970
Abdoulaye et al. (2018)	0.086	0.041	0.131	0.970
Abdoulaye et al. (2018)	0.080	0.035	0.125	0.970
Jaleta et al. (2018)	0.099	0.052	0.145	0.970
Etana et al. (2020)	0.086	0.017	0.155	0.920
Etana et al. (2020)	0.070	0.001	0.139	0.920
Etana et al. (2020)	0.415	0.343	0.487	0.920
Teklewold et al. (2017)	0.205	0.177	0.234	0.990
Teklewold et al. (2017)	0.060	0.031	0.088	0.990
Teklewold et al. (2017)	0.238	0.209	0.267	0.990
Assaye et al. (2022)	-0.087	-0.168	-0.007	0.900
Assaye et al. (2022)	0.194	0.113	0.275	0.890
Assaye et al. (2022)	-0.138	-0.218	-0.057	0.900
Assaye et al. (2022)	0.117	0.036	0.197	0.900
Tesfay (2020)	0.278	0.198	0.357	0.900
Dontsop Nguezet et al. (2012)	0.446	0.354	0.538	0.870
Dontsop Nguezet et al. (2012)	0.657	0.560	0.753	0.850
Dontsop Nguezet et al. (2012)	0.638	0.542	0.734	0.860
Aweke et al. (2021)	0.139	0.014	0.264	0.770
Aweke et al. (2021)	0.176	0.051	0.301	0.770
theta	0.081	0.058	0.104	

Source: Own elaboration form model results (2023).

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